Innovation Assessment via Information Markets

Experimental Studies of Illiquid Information Markets

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Abstract

The popularity and remarkable forecasting accuracy of Information Markets in the past decade made them very attractive to companies as well as organizations. Information Markets are online based market systems and utilize market mechanisms for the aggregation of information. Market prices can be interpreted to forecast outcomes of future events. While Information Markets were traditionally used in political or sports events, increasing usage in industry contexts is reported in scientific literature, for instance, to predict sales figures or project durations. Information Markets show impressive prediction accuracy and often outperform other forecasting methods and experts. However, Information Markets still have not become an established part of companies' forecasting strategies. In recent years, only a few reports about their usage in industry environments were published. Nevertheless, a promising application in companies is the usage of Information Markets for the assessment of innovations since it efficiently integrates many relevant people into decision making. In contrast to traditional methods like surveys, Information Markets constantly aggregate information once it becomes available and allow immediate interpretation of market results. Furthermore, performance based incentive mechanisms can be applied and trading in Information Markets is often perceived as entertaining by traders as well. However, there has only been little contribution to academic literature addressing the application of Information Markets in enterprise contexts.

In this work, experimental evidence for the assessment of innovations in companies is given. Results of a field experiment show that employees accept Enterprise Information Markets as a valuable method for innovation management. In addition, they are motivated to use them and, thus, market results show that employees assess innovation alternatives similar to an experts' benchmark. One of the main challenges is the size of Information Markets in an industrial context regarding the activity of participants due to the thread of low liquidity and, therefore, inefficient markets. Hence, another field experiment is introduced focusing on the successful operation of small-sized markets. In an investigation about trading behavior and activity it can be shown that permanent liquidity is essential in order to get continuous forecasts. Participants in an artificial market yielding liquidity performed ten times more transactions compared to a parallel market. Moreover, besides increased market activity the results of the market are more accurate as well as less error prone.

Summarized, this work provides results from two field experiments and shows that Information Markets produce accurate results given an appropriate market design – even in small-size markets. Furthermore, it demonstrates the successful application

in an enterprise innovation context. The consolidated findings of both experiment results provide a valuable reference for designing future Information Markets in industry contexts.

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Stephan Stathel

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List of Abbreviations

BN .... **B**usiness **N**etwork
BP .... **B**ritish **P**etroleum
CA .... **C**all **A**uction
CDA .... **C**ontinuous **D**ouble **A**uction
DPM .... **D**ynamic **P**arimutuel **M**arket
E.T. .... **E**xtra **T**ime
EIM .... **E**nterprise **I**nformation **M**arket
EIX .... **E**conomic **I**ndicators **Ex**change
FAQ .... **F**requently **A**sked **Q**uestion
FIFA .... **F**édération **I**nternationale de **F**ootball **A**ssociation
HSX .... **H**ollywood **S**tock **E**xchange
IEM .... **I**owa **E**lectronic **M**arkets
IP .... **I**ntellectual **P**roperty
MAE .... **M**ean **A**bsolute **E**rror
MM .... **M**arket **M**aker (Market)
MSR .... **M**arket **S**coring **R**ule
NGT .... **N**ominal **G**roup **T**echnique
NMM .... **N**on-**M**arket **M**aker (Market)
NYSE .... **N**ew **Y**ork **S**tock **E**xchange
PSO .... **P**enalty **S**hoot**o**ut
R&D .... **R**esearch & **D**evelopment
UEFA .... **U**nion of **E**uropean **F**ootball **A**ssociations
WSX .... **W**ashington **S**tock **E**xchange
XETRA .... E**x**change **E**lectonic **Tra**ding

Part I

Foundations & Related Work

1 Introduction

Forecasting has always been an essential method in decision making situations in times of uncertainty and doubt. Organizations and companies use forecasting methods to overcome these situations as one of the main challenges in the 21^{st} century. New products and technologies, globalization, shorter product life cycles, uncertainty, new trends as well as changes in law cause increased pressure for innovation and competitiveness (Urban and Hauser 1993). Especially in financial crises, where state-of-the-art methods show weaknesses and drawbacks, the capability of predicting future developments drives companies and organizations more than ever to develop and implement forecasting methods in order to better manage trends, potentials, opportunities, strengths and risks. Moreover, in innovation contexts making the right decisions is of utmost importance. Decision making about innovations is directly associated with estimations and beliefs of success in the future. Hence, strategic innovations, which will take effect in the future, can also be understood as a sort of forecasting task in order to choose which innovation is the most promising. Choosing a sub-optimal innovation strategy for instance may lead to substantial losses in market shares decreasing sales figures or earnings.

Today, executives and decision makers choose their actions based on vague information about future profitability of new products and services. They align their decision making with the company strategy supported by innovation life cycles to manage their innovation activities. Therefore, they need as much as information about future developments. One of the most crucial decisions is about innovation alternatives. Since the success of innovations can only be measured after the innovation is implemented, picking out the most promising one out of several sets the seal on companies' success in the future. For example, a study published in 2007 about technology innovations for cars state that until 2015, 800 billion Euro will be granted out of research funds to develop innovations. Approximately 40 % of it will be invested in unsuccessful projects and customers are only willing to buy 17 % of innovations offered (Dannenberg and Burgard 2007). Dannenberg and Burgard (2007) identify a serious economical deficit. They propose that car manufacturers as well as component suppliers should align their innovation management even more towards the needs of their customers.

Nowadays, executives discuss which innovation will be implemented in meetings based on forecasts developed by experts, consultants or externals. On the one hand, decision making solely based on forecasts from experts can be risky in case that experts or externals do not have direct contact to customers and vendors which can be of valuable information. On the other hand, sales employees often possess detailed information about expectations, requirements and needs of customers. It is therefore advantageous to integrate employees in order to integrate their information in innovation management (Spann and Skiera 2003; Soukhoroukova 2007; Chen et al. 2010). Furthermore, the combination of different methods for decision making and forecasting can be advantageous (Armstrong 2001). Armstrong (2001) claims that the combination of forecasts is in the majority of cases increasing the overall forecasting quality. From that point of view, adding further information from employees is promising in order to improve a company's innovation strategy. This implicit knowledge needs to be extracted, which causes a serious effort if many employees are involved. Therefore, an efficient method needs to be used, which is convenient to evaluate as well as capable of integrating ad hoc information. For instance, ad hoc information appears once estimations and beliefs of employees or experts changes. These changes must be represented instantly by an appropriate method in order to make it available for executives. Moreover, methods for the aggregation of information need to be continuous in order to integrate new information at any time. Traditional methods like surveys, meetings or Delphi studies are hard to operate in a real time manner.

In this work, Information Markets are introduced as a method to aggregate and assess estimations and beliefs about future events at once. Information Markets promise to meet the requirements of an industry context, e.g. an intuitive user interface, the application of incentive mechanisms for the participation as well as continuous analysis and interpretation.

In 1984, a connection between orange juice futures and weather was identified by Roll (1984). The futures' prices interpreted as predictor of weather forecasts were more accurate than the National Weather Service of the US Department of Commerce. In this case, the individual expectations of traders for orange juice futures were reflected in prices. That way, the interpretation of market prices can be consulted in order to derive weather forecasts. This example of the predictive power of markets gained popularity and was picked up in several fields of application. When Information Markets were firstly operated in 1884 for U.S. presidential elections they performed remarkably well at a time before the era of scientific polling had begun (Rhode and Strumpf 2004). Past 1940, no reports about the usage of Information Markets were published for almost 50 years. In 1988, the IOWA Electronic Markets Experiment[1] (IEM) picked up the concept of Information Markets again to forecast political elections with an online-based market system. Henceforward, results of Information Markets have outperformed benchmarks like polls, surveys or expert judgments regularly. In recent years, Information Markets have emerged strongly in the field of forecasting. The number of scientific reports about the method increased and scientists have experimented with Information Markets in different fields of application. For example, the usage in the field of sports predictions, for instance

[1] http://www.biz.uiowa.edu

STOCCER[2] or TradeSports[3], medicine or entertainment applications like the Hollywood Stock Exchange (HSX)[4], gained increased popularity. Several academics state that in many fields of application the results show a high prediction accuracy compared to traditional forecasting techniques (Pennock et al. 2001a; Spann 2002; Servan-Schreiber et al. 2004; Luckner 2008).

This development draws attention to organizations and companies in the late 1990s. Siemens used the market mechanism of Information Markets to forecast the completion of software development projects (Ortner 1997). Hewlett-Packard forecasted sales figures of printers and Ely Lilly assessed the market success of pharmaceutical products (Plott and Chen 2002; Polgreen et al. 2007). Other reports describe the successful usage of Information Markets for marketing purposes or the assessment of product innovations (Spann 2002; Soukhoroukova 2007).

Altogether, Information Markets operate similar to financial markets. Information Markets are basically a market system where futures about uncertain events are traded. Contracts represent events whereas market prices can be interpreted as probabilities for the outcome of an event. Traders in Information Markets buy and sell contracts based on their individual expectation about the likelihood of an event. Market prices therefore comprise expectations and beliefs of individual traders and are generated via the market mechanism. Traders perceive changes in market prices and update their own expectation based upon their available information, if they agree with the current market price or not. Otherwise they start to trade and put their individual information artifact about a future event into the market. Hence, an Information Market can be seen as a representation of the "Wisdom of Crowds", where aggregated information of several individuals shows more accurate results than of single individuals (Surowiecki 2004).

Once the real outcome of the predicted event is finally known, contracts are paid out according to payout rules. For example, the winning contract pays 1 currency unit and all other pays 0 if an event occurs. As a consequence, rational traders buy contracts if they belief that the likelihood of an event is undervalued in the market and sell them in case of overvaluation respectively. In efficient information markets, all available information is continuously reflected in market prices (Fama 1970; Fama 1991). Compared to traditional forecasting methods, Information Markets provide considerable advantages in terms of continuous forecasting, participation, cost efficiency, incentive mechanisms and analysis. The market mechanism aggregates information comprised in buy and sell orders automatically into the market price once two corresponding orders are executed. In contrast to Delphi studies[5], surveys or brainstorming sessions, the effort of analyzing results and managing the information aggregation is dramatically reduced. Due to the continuity of market prices traders interpret changes in prices caused by other traders immediately as new information. In turn, this motivates them to directly update their own expectations and to respond according to their own beliefs (Hanson 1999).

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

[3] http://www.tradesports.com, ceased operation in 2008

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

[5] Delphi studies are structured methods to aggregate group estimations over several rounds where feedback of each round serves as input for the next round. Refer to Section 2.2.3 for further details.

Therefore, markets need to be designed carefully in order to get appropriate results. Nuances in the market mechanism, user interface, market design or incentive mechanism influence traders decisions. Hence the market design needs to be engineered and an appropriate design is required (Weinhardt et al. 2003). Deficits in vital parts of the market system may lead to market failures and thus valuable market accuracy may get lost or results maybe distorted. Some evidence is reported in scientific literature stating that market failure may be consequence of structural drawbacks in market design (Schmidt et al. 2008).

In field of application with moderate public interest and especially in enterprise contexts, markets may suffer from illiquidity and low trading activity. In particular, in organizations where the forecasting object may be of bounded attractiveness compared to sport or political topics or topics that are very special so that only a small group may have relevant information, one can expect small-size markets. Furthermore, Information Markets are used in order to assess new product ideas and innovations. The challenge is that there is no real world event to benchmark the market results as it would be the case for sports or political events. That is why only a few innovations can be implemented out of several innovation proposals due to financial and strategic restrictions. Different payout mechanisms need to be designed or artificial benchmarks need to be created or consulted. In case of small markets, some reports describe the usage of automated market makers as liquidity providers in order to support low liquidity markets (Das 2005; Boer-Sorban et al. 2007). Automated market makers can be implemented as software agents following a certain trading strategy in order to react to market circumstances at any time as well as to keep the market liquid and, thus, attractive for human traders.

1.1 Research Questions

In this work, two main research objectives are investigated. First, an investigation about the effect of automated market making on the market quality is conducted as a means to an end in order to enable small-size Information Markets to produce useful results. Second, the results of the first research objective were used in a second field experiment for the assessment of innovation alternatives in a company, where small-size markets were expected in all probability.

The first research objective studies the impact of automated market making in Information Markets in the field of sport forecasting where Information Markets often proved to produce very accurate results. During the UEFA[6] European Soccer Championship 2008 a field experiment was conducted with two identical markets. The only difference was that one market employed an automated market maker whereas the other one did not. Trading data of both markets were analyzed after the experiment in order to measure the market quality improvements in forecasting accuracy, trading activity and market efficiency. Both markets were kept artificially illiquid in order to isolate the impact of automated market making on liquidity.

The main objective of this investigation is to provide evidence that Information Markets produce appropriate results even if they are small-sized and trading activity is relatively low. Moreover, the research on appropriate functionalities like

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

automated market makers is valuable in designing Information Markets for enterprise usage. Information Markets are powerful to aggregate asymmetric information from people if the topic of the market is of public interest. But sometimes Information Markets suffer from low liquidity, especially if Information Markets are about topics and events of moderate public interest. Therefore, the first research question investigates the impact of an automated market maker mechanism in Information Markets to support small-size markets.

> R1: Do Information Markets show more trading activity, increased accuracy, less error and higher information efficiency utilizing automated market makers?

In order to investigate R1, aspects like accuracy, trading activity and information efficiency are analyzed. Two identical markets are developed to forecast the results of the European Soccer Championship where the only difference was the employment of an automated market maker in one market. If automated market making fosters more accurate results, automated market making should be an integral part in further Information Markets where illiquidity could distort market results. The experiment design of the Information Market as well as the results are described in Chapter 4.

The second research objective of this work is about the usage of Information Markets for the assessment of innovation alternatives using the results from the first field experiment. As mentioned, Information Markets may be used in industry contexts to integrate employees or customers in innovation processes as an additional source of information for decision makers. The challenge here is to pay out contracts without having an outcome of an event. Therefore, an appropriate market design and incentive mechanism need to be engineered in order to assess the quality as well as the mode of operation of Information Markets. A field experiment was conducted in 2009 at EnBW Baden-Württemberg[7] in order to investigate the motivation of employees in participating as well as the result of the Information Market compared to the assessment of decision makers. Results of the investigation about the impact of automated market making were used in this experiment to keep the market liquid and attractive. The second research question in this work analyses the usage, the design as well as the operation of Information Markets in an enterprise environment.

> R2: How to design and operate Information Markets for innovation assessment in enterprises?

Assessing innovation alternatives and decision making about it are crucial tasks for decision makers because decisions in innovation contexts may have substantial financial effects for years. Furthermore, the analysis includes the identification of lead users. This type of traders is extremely important and interesting for companies in decision processes due to their empathy to the innovations which is reflected in their trading activity. Therefore, lead users can be involved in ongoing activities like

[7] EnBW is one of the fourth largest energy suppliers in Germany.

discussions, expert panels or consultancy. The design decisions of the market system for innovation assessment and the results of the field experiment are introduced in Chapter 5.

R1 and R2 amalgamate whenever an Enterprise Information Market (EIM) suffers from low liquidity. If not enough participants in a company are actively trading in the EIM and a trader wants to reveal his information in the market, there may be no counterpart to complete a transaction. At this point, the consolidated findings of the first research question (R1) provides valuable insights into the positive impact of automated market making in illiquid markets. The findings help to design markets for innovation assessment which motivate participants to trade while offering them a continuous possibility to integrate their information at any time.

1.2 Overview & Structure

This work is structured into six chapters. After the introduction, Chapter 2 provides an overview about the state-of-the-art in Innovation Management and introduces scientific approaches and experiments. In addition, promising new fields of application like Business Networks in combination with Open Innovation are described. Furthermore, commonly used techniques for the assessment of information by groups are briefly explained followed by challenges identified for the usage of Information Markets in innovation contexts.

Chapter 3 gives an overview on the fundamentals of markets in general and Information Markets in particular. The key functionalities and design aspects of markets are explained. Furthermore, a definition of Information Markets as well as their operational principles and theoretical foundations are described, especially about market liquidity and efficiency. Chapter 3 furthermore presents the current fields of application for Information Markets as well as traditional methods and the usage of Information Markets in organizations and companies. The chapter provides an overview about how Information Markets can be used and which design aspects have to be considered. Furthermore, Innovation Management in TEXO, which is a research project about the Internet of Services, is briefly introduced. In TEXO, innovation management plays a central role whereas the assessment of innovations via Information Markets is an important component in inter-organizational contexts.

Chapter 4 studies the impact of automated market making during a field experiment in order to forecast the results of the European Soccer Championship in 2008. The results show that the use of automated market making leads to higher trading activity, increased market accuracy and decreased forecast errors compared to the parallel run market without market making capabilities. Moreover, it can be shown that automated market making fosters increased information efficiency of small-size Information Markets.

Chapter 5 analyses the usage of Information Markets in an industrial innovation context. In 2009, a field experiment was conducted at EnBW Baden-Württemberg in order to assess innovation alternatives considering employees' opinions. The results show that Information Markets motivate employees to participate and reveal their individual information and beliefs about innovation alternatives. Furthermore, employees' implicit knowledge is a valuable additional information for decision makers which can be externalized via Information Markets. A lead user analysis is conducted to identify the most active and successful traders in order to integrate them into further steps.

Chapter 6 summarizes the overall contribution and discusses implications of this work. Furthermore, it identifies promising fields of application for Information Markets and proposes further research questions related to this work. Figure 1.1 illustrates the structure of this work.

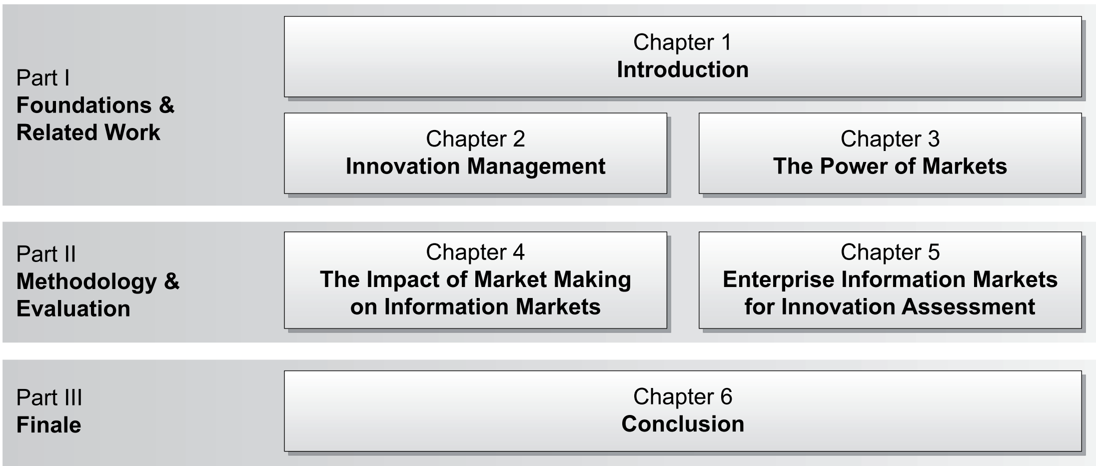


Figure 1.1: Structure of this Thesis

1.3 Related Publications

Parts of this work were reviewed and presented at scientific conferences and workshops as well as published in the respective proceedings and book chapters.

Concerning the results of Chapter 4, the results of the field experiment and the impact of automated market making were published in Stathel et al. (2008), Stathel et al. (2009) and Stathel (2009a). The prototype used to conduct the experiments described in Chapter 4 is explained in Stathel, van Dinther, and Schönfeld (2009) and Stathel, Luckner, Teschner, Weinhardt, Reeson, and Whitten (2009). Furthermore, the results were presented at the 3rd Workshop on Prediction Markets, Chicago, USA (Stathel et al. 2008), the PhD Summer School of the XVIII. International RESER Conference, Stuttgart, Germany (Stathel 2008) and the SMI Spring Workshop "Kollektive Intelligenz", Stuttgart, Germany (Stathel 2009b).

The results of Chapter 5 have been accepted for publication at the ICITIE Conference (Stathel et al. 2010). Furthermore, the concept and preliminary results of using Information Markets in innovation contexts were published in Stathel et al. (2008), Riedl, May, Finzen, Stathel, Kaufman, and Krcmar (2009), Riedl, May, Finzen, Stathel, Leidig, Kaufman, Belecheanu, and Krcmar (2009), Stathel (2009a) and Finzen et al. (2010). In addition, the TEXO Innovation Lifecycle for Service Innovation as well as results for innovation assessment were discussed at PhD Summer School of the XVIII. International RESER Conference, Stuttgart, Germany

(Stathel 2008) and the SMI Spring Workshop "Kollektive Intelligenz", Stuttgart, Germany (Stathel 2009b).

Beyond that, between 2007 and 2010, the research on Information Markets for innovation assessment was contributed to and reviewed within the THESEUS program[8] initiated and funded by the Federal Ministry of Economy and Technology. The work at hand is part of the research project TEXO[9] as a part of the THESEUS program that aims at creating a platform to foster the evolvement of a service platform of composable service modules. A relevant part of TEXO supports the innovation phase of services to support the creation of value-added complex services and enable their trade on the Internet.

[8]http://theseus-programm.de/en-us/home/default.aspx
[9]http://theseus-programm.de/en-us/theseus-application-scenarios/texo/default.aspx

2 Innovation Assessment

In this chapter, Innovation Management will be introduced in order to illustrate use cases where Information Markets can contribute to. In Section 2.1, the application of Innovation Management in enterprises will be outlined. Section 2.2 presents traditional methods for decision making to show the difference between them and Information Markets. Challenges in Innovation Management are introduced in Section 2.3.

Companies have been pursuing innovation management for years. To manage ideas with structured processes to support decision makers in a way that valuable ideas will not get lost. Often, employees have good ideas how to improve processes or organizational structures. Instead of disregarding these ideas, the ability to innovate is a key success factor for growth and competitiveness (Christensen and Raynor 2003). Getting ideas cannot be "enforced" or steered by structured processes. Therefore, many companies run idea submission platforms where for instance, employees can submit their ideas. SAP, for example, runs its Target Idea Management[1] in mySAP[2] to manage ideas from employees. Yet, companies complain that the rate of submitted ideas decreases over time and that it takes a long time before an innovation manager is able to review them. Furthermore, idea submission platforms are intransparent and lack real time feedback for submitters.

Several frameworks and approaches for idea and innovation processes exist in scientific literature. Wahren (2003) introduced an innovation process with the three phases: idea generation, evaluation and implementation. Wahren's process is one of the traditional examples of a structured process where generated ideas are screened by an innovation manager. Promising ideas are refined in further stages and finally implemented and used.

Hamel (2002) developed a model named "innovation wheel" in order to support the creation of ideas, its fast implementation and the subsequent user feedback

[1] http://www.target-soft.com

[2] mySAP is an e-business software integration tool that delivers content to the user based on his or her role in an enterprise.

to further improve the innovation. Small steps and continuous feedback lead to incremental improvement where promising innovations are encouraged and non-promising innovations are dropped. Thus, innovations will not come to a "final" state but stay in perpetual beta stages.

Soukhoroukova and Spann (2005) as well as Chen et al. (2010) successfully used Information Markets for the assessment of product innovations. Compared to conjoint analyses (cp. Green and Rao (1971)) and other techniques such as surveys, Information Markets employing 8-12 participants performed well and the results were more robust and reliable compared to a conjoint analysis with 307 participants. Hence, Soukhoroukova and Spann (2005) find that Information Markets seem to be suitable for the assessment of product innovations.

The assessment of new ideas and future trends is a difficult task since it is often based on vague information and uncertainty due to long forecasting horizons. Techniques exist for long term forecasting such as the Delphi method or Information Markets. A comparison of different methods for the aggregation of group members will be discussed in Section 2.2. The main result can be summarized as follows: Information Markets offer some advantages which can be exploited in innovation contexts regarding incentive schemes and information aggregation.

Information Markets only perform well if the market is liquid enough. However, sufficient liquidity can also be achieved given a quite small amount of traders (Soukhoroukova and Spann 2005). Yet, given a small set of participants, such liquidity is guaranteed if and only if the participants are motivated to trade actively throughout the whole market period.

2.1 Innovation Management

Today, companies have to face many challenges regarding innovation. Possible sources for innovation pressure are new products from competitors, arising trends and technologies as well as changes in legislation (Urban and Hauser 1993). Therefore, companies have to develop an innovation strategy which allows them to stay competitive and successful. In innovation contexts, all these aspects arising from the different challenges have to be considered in decision making. If decisions are not based on a solid information background, new products may be of minor success which may lead to substantial decrease in a company's reputation or monetary losses (Urban and Hauser 1993; Montoya-Weiss and Calantone 1994; Cooper 1999). In order to assemble a comprehensive base for decision making Information Markets are a promising method to integrate employees for the assessment of innovations, which will be shown in the following as an additional information source.

2.1.1 State of the Art in Innovation Management

An innovation consists of three components: innovation = idea + invention + diffusion (Corsten et al. 2006). Figure 2.1 illustrates the components. The first component of an innovation is the *idea*. An idea is a creative sudden thought, a notion. But even the very best idea is of little value without further development. In order to develop ideas, a structured approach is necessary to bring the idea to the state of an *invention*, which leads to the successful realization of a promising idea. This can be a prototype of a machine, a reference process or a product. The *diffusion* completes the innovation process. The diffusion of an innovation is for example the roll-out of a process or the market launch of a product.

Figure 2.1: From Ideas to Innovations
Adapted from Corsten et al. (2006)

The evolution from an idea to an innovation can be managed. Academia provides several approaches for Innovation Management. Every approach proposes a different way of how ideas shall be handled in order to optimally manage innovation processes. In this section, several existing approaches will be described.

There are different kinds of innovations depending on their areas of application. According to Hamel (2002), different types of innovations denote various levels of value creation and competitive defensibility. Hamel's innovation stack (cp. Figure 2.2) depicts different kinds of innovations according to their contribution to success while management innovations have the biggest impact on the organization followed by strategic innovations and so on. Later in this work, several innovations about business relevant topics are introduced in an industrial context (cp. Section 5.3). Most of them are on an operational level in that experiment.

Figure 2.2: Innovation Stack
Adapted from Hamel (2002)

2.1.2 Scientific Approaches

Today, there are several theoretical innovation processes. The necessity for the abundance of innovation processes today is the variety of companies which differs in size, corporate culture and organizational form. Therefore, each process model highlights different aspects of the innovation process and applies different focuses. Some of them were devised for incremental or radical innovations, others mainly depend on the type of innovation (cp. Figure 2.2). The majority of process models are tailored for product innovation. In the following, two popular scientific approaches will be described in more detail to get an impression of innovation management.

2.1.2.1 Innovation process of Wahren

Wahren (2003) breaks down the innovation process into three stages: idea generation, idea evaluation and idea implementation. Each of these stages is complex and consists of further phases.

The main aspect of the idea generation stage is the differentiation between three idea pools. The first pool (I) collects all submitted ideas, the second Pool (II) collects only mature, comprehensible and properly described ideas which reach the second stage for evaluation. If an idea cannot be complemented and has no value, it is forwarded into the trash which is Idea Pool III. According to the innovation process of Wahren, the idea evaluation stage is the most important one and contains three Phases in which ideas are further analyzed and filtered. Figure 2.3 shows the model.

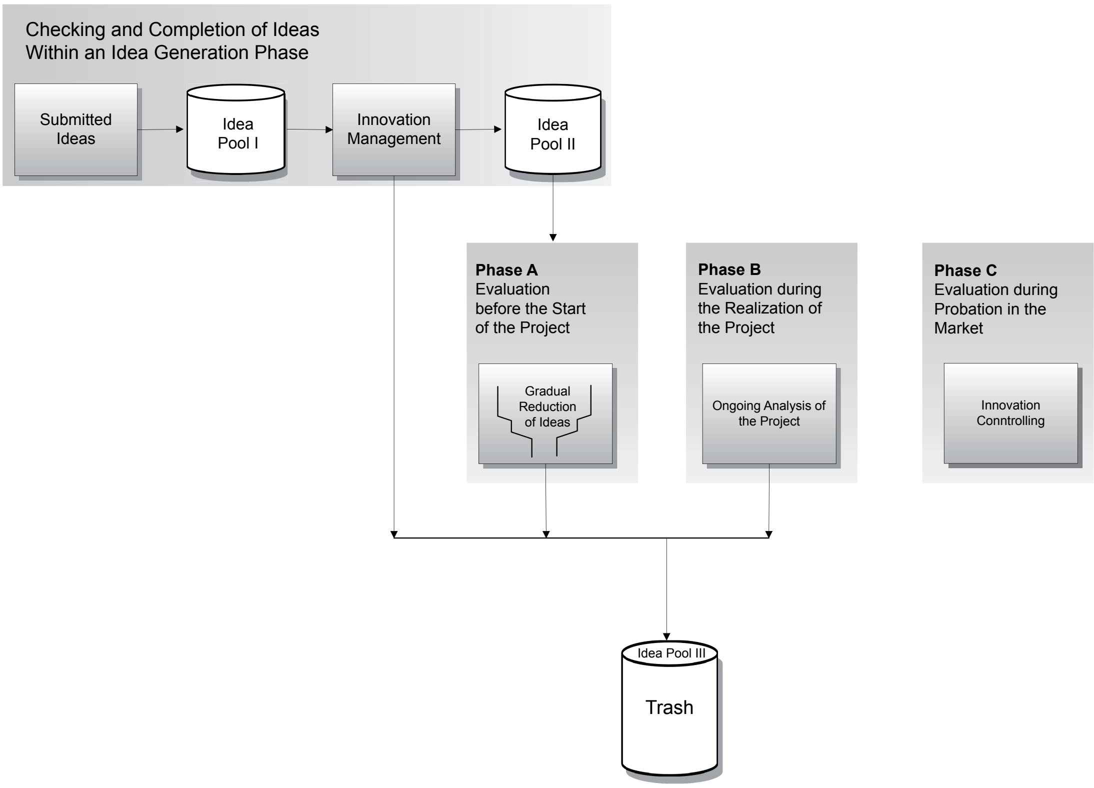


Figure 2.3: Idea Evaluation and Innovation Life-Cycle
Adapted from Wahren (2003)

Phase I – idea evaluation before the start of the project: First, the complemented ideas in Idea Pool II are filtered using pro and contra lists, checklists or by organizing workshops. At this point, Information Markets can be used in order to filter them and use expectations and beliefs of employees from their individual point of view. Wahren states that this rough evaluation sorts out approximately 50 % of all ideas. Afterwards, further evaluation steps are carried out. The remaining ideas have to be analyzed in details. Following this analysis, only 30 % of the original ideas remain. The last revision ends with the detailed cost-benefit analysis, according to which a maximum of 20 % of the overall ideas (from Idea Pool II) can be approved for implementation. As mentioned, the process of selecting promising ideas can also be supported via Information Markets.

Phase II – evaluation during the realization of the project: In the second stage of idea evaluation the 20 % of the residuary ideas are evaluated during their implementation. It is an empirical fact that 50 % of these ideas will be rejected.

Phase III – Evaluation during probation in the market: Innovation controlling deals with the idea evaluation either immediately after the project has ended or within the probation period. Wahren distinguishes between evaluation on the economic and procedural levels. The economic level monitors the achievement of the objectives and the sufficiency of the resources used by analyzing the number of employees involved in the project, the time invested in the project as well as the overall project expenses.[3] This information is a crucial factor for future projects because an innovation proves itself only after a certain period of time.

The innovation process proposed by Wahren is a generic approach to innovation management that is independent from the idea/innovation type and the application area. It covers all stages of idea development from idea generation to receive feedback about realized ideas. The innovation process is transparent, well-structured and systematic due to predefined activities and execution sequence, which are open and visible to everyone. Nevertheless, its idea evaluation sub-process (Phases I-III) and its criteria are not precisely specified. Because of the determined innovation lifecycle, Wahren proposes to shorten the idea processing time. However, he does not define any thresholds which would fix the execution duration of each phase. There is also no role allocation that defines responsibilities for individual tasks and what impact they have on the entire innovation process. Neither a possible collaborative idea development nor an appropriate reward system is taken into account.

Considering the reward system, Information Markets can be used during the evaluation phase as a collective tool for the assessment of innovations. Via the supported incentive mechanism, the participation in the assessment of innovations can be rewarded based on the individual performance and activity of each participant. Furthermore, the assessment via Information Markets is transparent to all participants and the assessment can be conducted via a community, which is advantageous in decision making (Füller et al. 2004; Surowiecki 2004). Thus, Information Markets can be a valuable tool for the assessment of ideas.

2.1.2.2 Innovation Wheel of Hamel

The innovation process provided by Hamel (2002) exhibits four fundamental components: design rules for a radical innovation, innovation as a capability, innovation

[3]In this context, Siemens used Information Markets to forecast project durations (Ortner 1997).

as a process and principles of effective activism (cp. Figure 2.4). Hamel's innovation model primarily aims at radical innovations. Radical innovations in contrast to innovations for continuous improvement are characterized as several significant changes in multiple aspects of a product or service. For example, running cars with fuel cells would rather be considered a radical innovation than improvements in fuel efficiency of conventional combustion engines. Hamel defines "Design Rules for Radical Innovation" and describes "Activism" which are of minor importance in this work and will not be discussed.

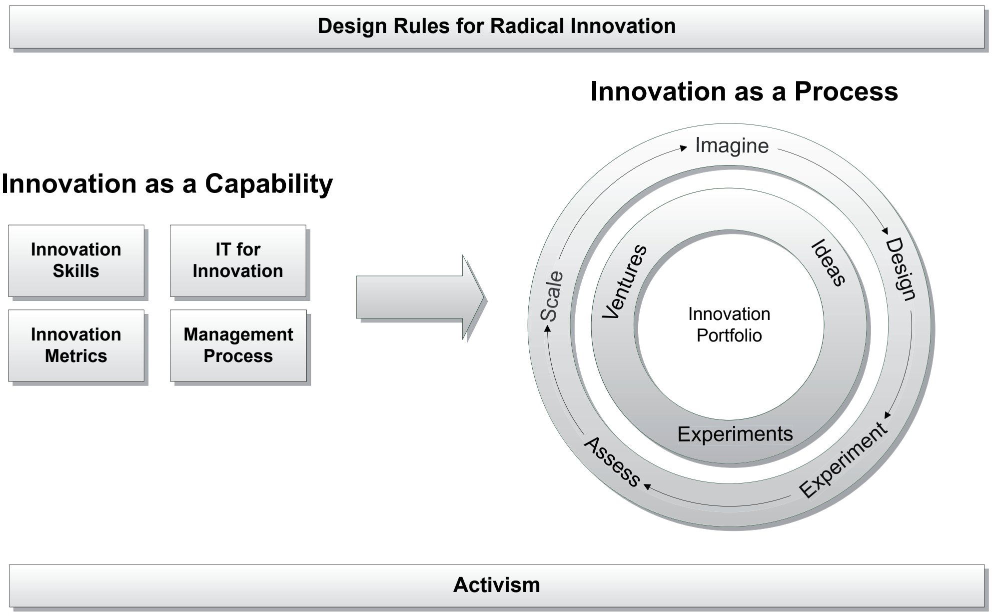


Figure 2.4: Innovation Wheel
Adapted from Hamel (2002)

For this work, the interesting part is "Innovation as a Process" which is supported by the capabilities a company need to have such as the capability to develop and implement innovations (Innovation Skills), provide appropriate IT support for innovation tasks (IT for Innovation), develop adequate metrics to assess innovation capabilities and value, as well as efficient management processes to support innovation activities (Management Process). These capabilities support "Innovation as a Process" as a closed loop for innovation management. The steps are similar to the previously mentioned approach, starting with the idea creation and design phase.

The process is initiated with the idea development and design phases (Imagine, Design). Once an idea is designed, small-scale experiments on a conceptual basis are conducted in order to gather further insights about their value (Experiment). The results are assessed (Assess) and finally the decision has to be made if the idea will reach the next stage which can be further tests like large scale experiment or a prototype. In this case, the "enveloped" process will start again with the five phases in order to scale ideas till they reach a state where they are ready for the market or the organization. Thus, the core idea of Hamel is to run the outer process several times and on each cycle develop the idea further to a higher level. If an idea fails the requirements, which increase on each level, it will be discarded.

Hamel's concept embraces the entire life-cycle of an idea several times, accompanying it through its multiple transformations on the way to innovation. Even though the innovation process is open and comprehensible, it is highly abstract without a detailed view of the entire process. Especially in strategic decision situations it is important to integrate different perspectives from employees, customers or vendors. Hamel does not mention which single tasks are to be executed by different persons and that all participants need to be motivated and rewarded in order to trigger a further contribution by them. The difference to Wahren's innovation process is that Hamel implements a closed loop in order to provide continuous improvement and scaling of innovations. After an innovation cycle is accomplished, it starts anew with a new cycle to improve the achievements of the last cycle and scale ideas to a higher level.

In Hamel's model, Information Markets can again be used as a method of specialization during the experiment and assessment phase while providing instant feedback. Furthermore, Information Markets incentivize participants via the performance-based incentive and reward mechanism. In Section 3.4.3.1, a continuous innovation management framework will be introduced developed in a research project. The innovation management is similar to the above mentioned scientific approaches. In every stage of an innovation life-cycle, methods and concepts are developed including an Information Market approach to assess ideas before they are realized in subsequent steps. In the next section, scientific experiments utilizing Information Markets for the assessment of product ideas will be described.

2.1.3 Scientific Experiments

Scientific publications on Information Market usage in innovation contexts are scarce – or have not been made public due to confidentiality about the usage. In the following, two of them will be briefly explained.

In the first one, "Idea Markets" were used to generate product ideas and assess them via a market system (Soukhoroukova 2007). It aims to assess the consistency with traditional methods in product planning for a company. In this experiment, participants were allowed to post their ideas directly in the market as contracts. The market ran 36 days and was open to all employees. The 10 most successful traders regarding their trading performance were remunerated with 3.000$ in total. Traders were endowed with virtual money. Furthermore, traders could submit ideas for several categories: (a) new technologies for the company, (b) new product ideas for a specific product category, (c) innovative product- and business ideas for the company. Traders had to compose their initial portfolio of shares at market start. Traders had to buy their portfolio items once they assessed a submitted idea promising. After reaching a minimum investment threshold, contracts were kept in the market and were not removed due to moderate quality or low popularity. Altogether, the market results showed an acceptable consistency with the results of traditional methods in product planning.

The usage of Information Markets was also reported in an enterprise innovation context in order to demonstrate the applicability of Information Markets in innovation contexts (Chen et al. 2010). In total, this market addressed about 700 employees whereas 64 registered to the market. 61 employees were considered active in the market, that is, traded at least once. The market was available for 2 weeks and about 3.200 trades were counted. In total, 17 contracts were traded representing emerging technologies. As a benchmark, Chen et al. (2010) used an expert panel assessing 6 out of the 17 contracts. After the market closed, the final market prices were taken to compare them to the results of the expert panel. Unfortunately, there is no further information about why the experts only assessed six contracts. Furthermore, the authors did not describe exactly how they closed the market and how they come to their interpretations of the results. Overall, several details are missing in order to understand the experiment design or repeat it.

Apparently, there is a research gap in the usage of Information Markets for innovation assessment – especially in business contexts. Questions like payouts for traders, the composition of traders and how traders are supported with additional information or communication methods need to be further investigated. In the next section, a recently transformation process in companies will be briefly described. Companies begin to open themselves for innovation coming from the outside, which is important for customer integration. Innovation is no longer limited to be conducted by R&D departments and therefore extents the application of Information Markets for inter-organizational contexts.

2.1.4 Business Networks

During the last decade it could be observed that companies focused on their core competencies and sold off business units which were out of scope. This has led to a highly specialized economic landscape. For instance, the value creation in the automotive industry was at only 35 % in 2002 and is estimated to decrease to 23 % in 2015.[4] The traditional value chain transforms into so-called Business Networks (BN) in which enterprises collaboratively work together (Steiner 2005).

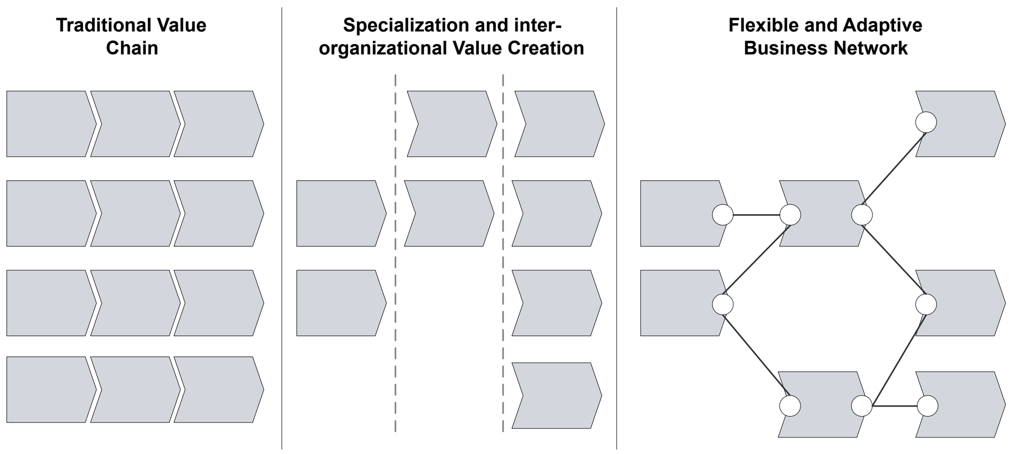


Figure 2.5: Transformation to Business Networks
Adapted from Heuser et al. (2007)

[4] Mercer Consulting Study “Future Automotive Industry Structure (FAST) 2015”

Nowadays, the transformation from hard-wired value chains into specialized parts of a business process is intra-organizational. Therefore, other companies specialize in certain parts of a value creation process. Together, several companies can create value through combining or concatenating their process parts. The collaboration of several companies offering their specialized parts leads to a flexible and adaptive Business Network (cp. Figure 2.5). Once a Business Network is established, innovation processes covering certain steps of value creation need to be managed. The communication between involved companies in innovation activities gets cumbersome for large-scale Business Networks. The assessment of innovations in the value creation process can hardly be accomplished via Meetings or Delphi studies due to their processing time. As an alternative, Information Markets can be used offering advantages such as the ad hoc integration of assessment results from several people continuously or an performance-based incentive mechanism. Furthermore, Information Markets provide transparency of traders' assessments about innovation alternatives at any time. It is easy to integrate people from different companies via Information Markets due to the continuous information aggregation capabilities in an online-based web application. Thus, it can be used by executives to constantly track the assessments of traders and to use this estimations for decision making. Information Markets are therefore promising to be further used in inter-organizational innovation contexts.

Besides the opening of companies to create value in BNs, also innovation processes have to be conducted by involved companies. Therefore, "Open Innovation" describes the ability of companies to open their innovation processes where Information Markets can deliver a valuable contribution by integrating stakeholders, for instance regular employees, executives and decision makers.

2.1.5 Open Innovation

The term open innovation was introduced and made popular by Henry Chesbrough (Chesbrough 2003; Chesbrough 2006). Open innovation in general means to open the innovation process of a company. Thus, the firm is given a lot more possibilities how to deal with innovation. As shown in Figure 2.6, open innovation can take place in both directions.

First, from inside of the company to outside, and second, the other way round. The direction from inside the company to outside stands for the company opening itself to sell its intellectual property to other firms. "Open innovation is characterized by cooperation for innovation within wide horizontal and vertical networks of universities, start-ups, suppliers, customers and competitors. Companies can and should use external ideas as well as those from their own Research & Development (R&D) departments, and both internal and external paths to the market, in order to advance their technology" (Laursen and Salter 2006). As Chesbrough (2003) reveals, most of the intellectual property (IP) slumbers in the company and never gets used. IP can be divided into different categories. First, IP that is currently used and on which the innovations of the company are based. Second, IP that is held back due to strategic reasons. Third, IP that was discovered and patented but never used. One can divide the last type into IP that can be of use for the company and IP that has nothing to do with the company's core business. Chesbrough

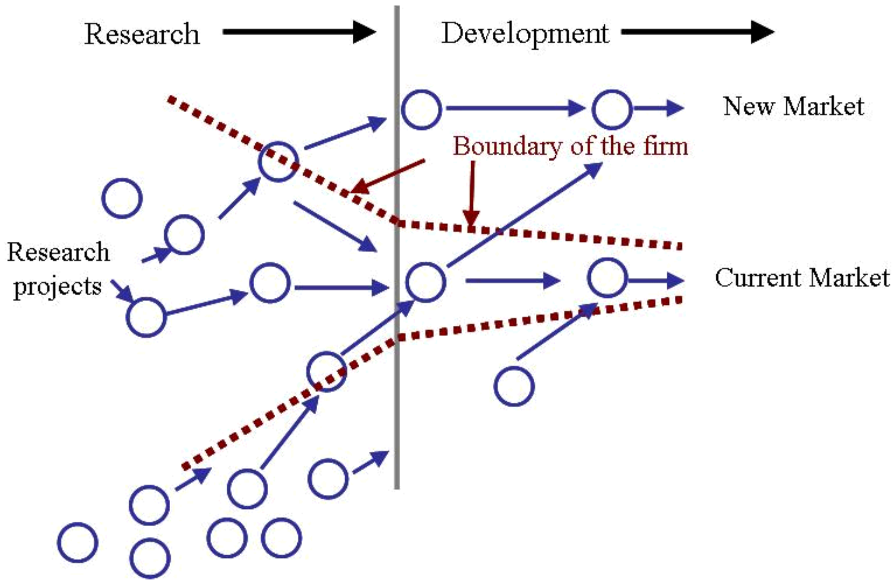


Figure 2.6: Open Innovation
Adapted from Chesbrough (2003)

(2003) holds the opinion that the company can definitely sell IP of type three and IP of type two in some cases. On the one hand, the company would benefit from additional income through more openness. On the other hand, the society on the whole would benefit. It is also possible that there are several companies that are not able to do comprehensive R&D or cannot use specific processes due to patents held by another company not using the IP. A lot of innovations would have never been discovered if the company holding the IP had not sold it. In Figure 2.7, the traditional way of innovation is shown which is called "closed innovation".

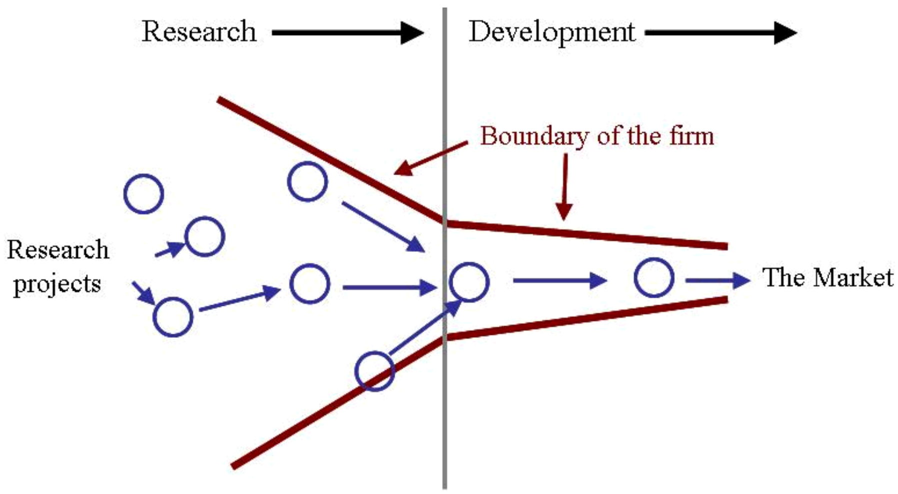


Figure 2.7: Closed Innovation
Adapted from Chesbrough (2003)

In this concept, all three research projects, new business development and the marketing of new products takes place within a companies' boundaries. An important difference of the open innovation model to the closed innovation model is that it has no firm boundaries and, hence, allows a diffusion of intellectual property both from outside the company to the inside and the other way round. “Open innovation means that valuable ideas can come from inside or outside the company and can go to market from inside or outside the company as well” (Chesbrough 2003). Companies search on the one hand outside the organization for new technologies and ideas and on the other hand cooperate with suppliers, competitors and customers to create customer value. Thus open innovation can be described as combining internal and external ideas and using internal and external knowledge to create new products and services (Chesbrough 2003). An important aspect in this case is collaboration. Innovation is almost never developed by only one individual. This is mentioned by Berkun (2007) in his book “The Myth of Innovation” where he describes this fact as “wise innovators [. . .] initiate partnerships, collaboration, and humble studies of the past, raising their odds against the timeless challenge of innovation”. But companies do not only let this IP diffuse into the company, they also give IP away by selling patents or the rights of usage to external companies.

The fact that companies open themselves to search and use external IP and ideas sets the founding stone for the whole e-customer integration concept. The open innovation model can be seen as a rethinking of the companies to more openness. They start to use the customer to get new ideas for the development of new innovative technologies and products. Piller (2008) goes further and states at an interview that “companies that adopt an open innovative approach have to recognize that ’not all the smart people work for my company’.” (Piller 2008). The importance of the open innovation approach is increasing and is adopted in more and more businesses. ”This approach places external ideas and external paths to market on the same level of importance as that reserved for internal ideas and paths to market during the closed innovation era” (Chesbrough 2003). The concept was further developed and described by von Hippel (2005). It stands in contrast to the traditional act of production: “The user-centered innovation process [. . .] is in sharp contrast to the traditional model, in which products and services are developed by manufacturers in a closed way, the manufacturers using patents, copyrights, and other protections to prevent imitators from free riding on their innovation investments” (von Hippel 2005). There are a lot of examples of “traditional” companies using the new open innovation concept. Procter & Gamble (P&G) for example has the target of sourcing out 50 % of its innovation from outside the company. Other examples are QinetiQ, Shell, DSM or Tate&Lyle. The examples of these companies suggest that a lot of non-Internet companies are using this concept successfully (Gaule 2006). Reichwald and Piller (2005) illustrate how the open innovation concept is connected with the concept of customer integration. As shown in Figure 2.8, the closed innovation concept represents the “old” way of how to treat a customer.

In “mode 1: listening in” the customer/user is only passive. The companies produce and design products for their customers. There are two types reflecting the interaction with the customer. The first type is the indirect collection of market/customer information where the customer does not even recognize that the company aggregates information. The second stream goes more into the direction of the customer but also without the customer’s recognition and intention to submit his needs. The customer is not active in this mode in contrast to the next step, an intermediate step between the closed and the open innovation concepts, where the

Manufacturer-Customer Interaction in the New Product Development Process		
Mode 1: Listening in: Using customer data from search portals, web-based advisors, or product catalogs to explore unmet customer needs ("*design for customers*")	**Closed Innovation**	**Indirect collection of market / customer information** • Evaluation of literature and trade journals of customers' industries • Evaluation of patents • Evaluation of feedback based on analysis of CRM systems etc.
		Customers as passive target of observation • Customer observations (during use of product) • Empathic design • Click-stream analysis, web-based content analysis etc. • Exploring search mechanisms, searches in product catalogs
Mode 2: Asking about: Asking customers explicitly about new product features or product concepts, using surveys, web-based conjoint analysis, and other means to get access to customer preferences and needs ("*design with customers*")		**Manufacturer initiated dialogue with customers** • Customer / user panels; user surveys on (future) requirements • Consumer idealized design • (Web-based) conjoint analysis • Quality function deployment and Kansei engineering • Securities trading of concepts (virtual stock markets) • Creativity workshops with customers • (Virtual) concept testing and prototyping • Piloting and field tests, (web-based) critical incident technique • Product clinics (also in form of online discussions)
		Customer initiated dialogue with manufacturers • Evaluation of complaints • Evaluation of customer requests / customer recommendations • Systematic complaint management • Screening of user groups and user communities
Mode 3: Taking part: Allowing and enabling customers to design their own solution (at least partly) by the use of user innovation platforms ("*design by customers*")	**Open Innovation**	**Customers are equal partners of the organization** • Manufacturer initiated and operated toolkits for innovation • Intermediary initiated and operated toolkits for innovation • User design: Using visual drag-and-drop, respondents trade off features against price or performance • Joint product development with customers (lead users) • Temporary employment of supplier's staff at customer • Temporary employment of customer's staff at supplier • Lead user workshops initiated by the manufacturer
		Customers as independent innovators • Lead user activities without initial motivation of manufacturer • Community innovation (e.g. open source) • Customer initiated and operated platforms / toolkits for innovation

Figure 2.8: Open vs. Closed Innovation
Adapted from Reichwald and Piller (2005), based on Dahan and Hauser (2002b)

customer can interact with the company but is also passive. The way companies interact with customers is seen more from the marketing point of view where the needs of the customer are evaluated with surveys. This approach integrates the customer who is still passive. Companies are willing to give customers the right to have a say in a matter, but they do not commit themselves to use or implement the customer's ideas into their new products or services. There exist two different types in this mode, too. The passive customer approach is that the company initiates the dialogue with the customer. That is the described marketing approach where the needs are evaluated. A more active approach is the customer being active and initiating the dialogue with the company through feedback and complaints. But this also does not reflect the e-customer integration concept. Finally, the next step, the mode "Taking part", reflects this concept. In this mode products are "designed by the customers" who have the possibility to create their own solution. This mode is also divided into two steps. The first step is the customers being equal partners of the organization. They are included into company processes through "Toolkits for User Design" initiated by the company. They can compose products out of specific components and are also deployed as temporary staff at the company.

As one can see from these examples the customer takes over more tasks during the product development process and can be seen as a really active customer. The second step described is the customer as independent innovator. This type of customer is becoming active himself and initiates the interaction. Examples are the lead user concept, community innovation as for example the open source concept and customer initiated and operated platforms.

In Open Innovation, there is high potential for the usage of Information Markets. Even customers can be integrated with low effort once a web-based market system is established. Further customers can be added to extract their implicit knowledge about innovation alternatives continuously via the aggregation capabilities of a market mechanism. Moreover, multiple companies can be addressed for inter-organizational innovation processes in BNs. The application of Information Markets offers notably advantages to traditional methods for decision making, which will be described in the next section.

2.2 Traditional Methods for Decision Making

As Information Markets gained attention as a method for organizational decision making, it can be used to complement established methods. Established methods are Delphi Studies, Nominal Groups and Meetings. This section introduces the state-of-the-art methods used for decision making.

2.2.1 Meetings

Meetings are the most common approach for decision making and forecasting in organizations. People meet directly and interact with each other personally. Meetings are organized with agendas about what will be discussed. Therefore, participants prepare themselves in order to argue their position on a topic. Finally, a consensus derived by group members is the result of a meeting. Meetings have shown to be prone to many biases and drawbacks (van de Ven and Delbecq 1971; Graefe 2009):

- Time and effort for a group to maintain itself (Dalkey and Helmer 1963)
- Tendency to aim at reaching "speedy decisions" and not to consider all problem dimensions (Maier and Hoffman 1960)
- Tendency to pursue a limited train of thought, which leads to a "central tendency effect" or "group think" (Janis 1972)
- Less confident group members or people from lower hierarchies may stay silent because of group pressures for conformity or implied threats of sanctions (Dalkey and Helmer 1963)
- Dominant personalities tend to exert excessive influence on the group (Dalkey and Helmer 1963)
- A "self-weighting" effect occurs: group members try to participate and to exert influence to a level that they feel equally competent with others (Kelley and Thibaut 1954)

In scientific literature, there is only little evidence that Meetings are preferable for decision making or forecasting (Armstrong 2006). Concerning the acceptability, Meetings are accepted due to personal interaction which people consider as satisfactory. People enjoy working together and Meetings have shown to achieve a high level of satisfaction (van de Ven and Delbecq 1974; Boje and Murnighan 1982).

2.2.2 Nominal Groups

The Nominal Group Technique (NGT) is a further development of Meetings in order to mitigate drawbacks of Meetings by adding a structured format. The NGT was developed by van de Ven and Delbecq (1971) and van de Ven and Delbecq (1974). The NGT follows three steps:

1. Group members work independently and generate individual estimations on a problem
2. Group members come together and discuss in an unstructured fashion about their solutions
3. Each member works again independently to provide an individual estimate

After these three steps, the individual estimations are aggregated and build the final result of the group. During the second step, group members get feedback after they build their own estimate and can discuss it with other members in order to validate, whether they have to update their point of view or whether they are in line with the group estimate. This step helps to come to more informed decisions. In the third step, members do not have the chance to interact again in order to improve their estimates again. Advantages to van de Ven and Delbecq (1971) are:

- Through incorporating direct interaction and presence of others, NGT provides evidence of activity and retains the social facilitation of the group process
- It eliminates evaluation or elaborating comments when generating the problem dimensions
- It provides participants with time for reflection and forces them to record their thoughts
- It limits the influence of dominant personalities on the group outcome by involving the judgments of all group members

2.2.3 Delphi Study

Participants in Delphi Studies are not required to meet personally, as it is usual in Meetings or NGT. The Delphi Study avoids some major shortcomings of Meetings or NGT and is seen as the state-of-the-art and most developed method for forecasting. Compared to NGT, Delphi Studies avoid direct interaction to eliminate every social bias and to keep participants anonymous. The method was developed in the late 1950s. Delphi Studies are multiple round surveys in which every participant reveals his own individual estimates about a problem, enriched with comments from the prior round consolidated by the operators. After each round, individuals are faced with the aggregated results of other individuals anonymously. Taking this intermediate result into account, a new estimation is provided in the following round. In the final round, the group result is the aggregated outcome of the individual estimates. The strength of this method is the structured communication process that enables discussion and helps to achieve a group result free of the major drawbacks of Meetings of NGT (Woudenberg 1991; Rowe and Wright 1999; Rowe and Wright 2001).

Compared to Information Markets, the Delphi method shows some similarities (Rowe and Wright 1999; Graefe 2009):

1. Both are structured approaches that use a set of predefined hypotheses
2. These hypotheses are judged anonymously
3. Both methods incorporate feedback. However, the nature of feedback differs. Delphi feedback can also reveal comments and reasons for estimates[5]
4. The objective of both mechanisms is to achieve an aggregated group result

Altogether, Information Markets can be expected to have some advantages over the Delphi method. Information Markets are highly scalable for a large group of participants. The results do not need to be aggregated manually or semi automated. The market mechanism works as aggregation mechanism. Furthermore, the market mechanism is capable of integrating new information continuously, whereas the Delphi method is round-based and only reveals estimations once the outcome of each round is aggregated.

Delphi uses an iterative process of distributing questionnaires to collect experts' opinions, aggregating the data and presenting the results to the sample group along with a new questionnaire. Information Markets, on the other hand, rely on the fact that diverse information can be carried and aggregated in one single attribute – the price. Green et al. (2007) compared both methods to elicit forecasts from groups. In contrast to the Delphi method, Information Markets offer the advantage that the results (i.e. valuations of the participants) can be interpreted immediately and continuously. Therefore, new information can be integrated immediately and trading itself is often intuitively understood by the participants. Furthermore, Information Markets are often considered as a method to support "Wisdom of Crowds" because they aggregate information held by many people (Surowiecki 2004). On the other hand, trading in Information Markets gets cumbersome for large studies with many questions and low liquidity in small-size markets. The use of Information Markets in the context of innovation processes and forecasting appears advantageous since the participants do not have to exhibit their complete knowledge. Thus, participants use their information at hand to gain profits from stock trading and report their opinion indirectly. For a deeper discussion about the comparison of both methods refer to Green et al. (2007).

[5]In Information Markets, feedback can also be supported via chats or blogs. By today, no published research investigated the effect of feedback in Information Markets.

2.3 Challenges & Summary

In Innovation Management, complex decisions require the involvement of nearly all departments of a company. In order to stay competitive and innovative, it is necessary to involve the top management as well as employees frequently having direct contact with customers, suppliers and business partners. Therefore, it is important to create a company culture allowing that all stakeholders in innovation contexts communicate and exchange information about innovations to find the best decision as a consensus of a all managers, executives and employees involved. Group decisions are in some contexts preferable against individual decisions (Lorge et al. 1958; van Bruggen et al. 2002; Ozer 2005). One of the main challenges for the application of Information Markets is, therefore, the involvement of relevant stakeholders.

Successful Innovation Management depends on a healthy company culture, which is a challenging task in itself. Therefore, the company culture must support innovation activities “bottom up”, that is, employees need to be involved in decision making. Furthermore, centrality in decision making reduces the exploratory innovation capability of companies (Jansen et al. 2006). In other contexts, Information Markets have already been used for improved decision making in software development processes (Ortner 1997). The involvement of employees in decision making and asking them about their estimation and beliefs about the future may be problematic due to the alignment with the company culture. But some reports find that Information Markets are more likely to improve than detract from workplace culture because employees perceive it as positive to be involved in decision making processes (Abramowicz and Henderson 2007). Thus, providing a well-disposed company culture where employees are motivated to participate in innovation contexts is one of the most essential challenges. This will not be further discussed in this work, whereas the results in Chapter 5 show that the involved company during the field experiment provided a business culture in order to conduct the field experiment successfully and Information Markets were accepted by employees.

Before the experiment results are presented in Chapters 4 and 5, the basics of market systems, Information Markets as well as their design is described in the next section. It gives an overview about the design parameters of Information Markets and illustrates its successful implementation in several fields of application.

3 The Power of Markets

For years, markets and auctions have been the methods of choice to exchange goods, products and services (Smith 1966). With the rise of the Internet several years ago, markets are no longer limited to traditional physical sites or auction houses – markets are everywhere. Through eBay, in particular, mostly every Internet user has gained some “market experience”. Therefore electronic markets can be rated as commonly accepted by people. Furthermore, it has become common for banks to provide online access to stock markets, thereby offering online brokering capabilities with millions of small investors trading every day.

3.1 Evolution of Markets

The concept of trading, price setting and exchanging goods is known to be an efficient way to determine the worth of goods for a long time (Smith 1966). During specialization and the division of labor, goods were no longer exchanged between individuals only. As currency established and goods could be valuated in a consistent and comparable unit. The introduction of money changed the way of determining the worth of a good. The valuation of a good depends on changes by each individual based on the actual situation and context. Varian (1992) states, as an example, that a famished man on a lonely island with no food is willing to pay 10.000 $for a can of vegetables to avoid dying. On the other hand, a can of vegetables in supermarket can be bought for a few cents. The difference is the situation on the lonely island which drives the man to pay more money than usual.

Markets are used to determine the value of goods. By using money, the price can be negotiated by buyers and sellers and once they found an equilibrium, the trade can be settled. Every individual in this negotiation process has individual preferences upon it builds its valuation. Furthermore, information plays an important role in the negotiation process. Having superior information about a good, the finding of the individual worth is easier than to think about a common price. For example, buying the Mona Lisa involves the danger of falling for an imitation. Hiring an expert who issues a certificate about the authenticity of the painting, one can be sure not to buy an imitation. In this case, the information has to be bought – maybe for a lot of money – in advance in order to avoid a misinterpretation of the valuation.

Similarly, in modern financial exchanges like the New York Stock Exchange (NYSE) or the Deutsche Börse/XETRA, markets are used to determine the value of companies. The valuation of companies is very difficult and the determination via market mechanisms is the best known estimator we know in order to determine the true value (Plott and Sunder 1988). In other words, markets are like search engines, in which traders search for the best price or where they should invest their money. Therefore, market participants interact through the price mechanism of markets which means that supply and demand is evaluated via prices in a negotiation which may come to an equilibrium (Harris 2003). Therefore, market prices can be used in decision processes. Based on the price, market participants can decide whether to allocate resources or not (Hayek 1945).

Modern markets are often designed in *auction* formats. Popular examples are financial stock exchanges like the NYSE or the Deutsche Börse/XETRA. In an auction, buyers and sellers communicate via price offers to buy or sell respectively. These orders are stored in a so-called *order book*. Once a sell offer is lower than a buy offer, both offers overlap regarding the price and can be executed. The execution can be done in different ways. The two most common procedures are continuous execution and periodic execution (Madhavan 1992). In continuous market systems, incoming buy and sell orders are executed once they match a corresponding offer. This is called Continuous Double Auction (CDA). In a periodic auction, offers are stored in an order book and are matched periodically. Periodic auctions are called Call Auction (CA). Following the Market Engineering approach, which is described in Section 3.1.3, the auction type needs to be designed carefully based on the objective of the market. For example, transaction prices in a CDA reflect all currently available information once a transaction is executed. Private information[1] represented in orders from other traders then becomes public information in the new market price and is therefore no longer visible as a buy or sell order to others. In a CA, all orders are stored until they are executed. Therefore, a CA can lead to different market results as markets in which trading takes place sequentially (Madhavan 1992). On the other hand, a continuous auction can be executed faster and traders realize the Market Outcome immediately (Forsythe et al. 1982). In most financial exchanges, the CDA as well as the CA mechanism is used. Depending on the market objective, different market mechanisms may be considered (Harris 2003; Schwartz et al. 2006).

3.1.1 Efficient Markets

It is assumed that the price comprises historic, public and individual information about the fundamental value (Fama 1970; Fama 1991; Schwartz et al. 2006). The fundamental value of stocks is the value that all traders would agree upon if they knew all available information and if they could properly analyze it. Informed traders tend to know if the fundamental value is under- or overvalued whereas

[1]Types of information are described in Section 3.1.1.

uninformed traders do not know if stocks are fundamentally over- or undervalued (Harris 2003).

For example, historic information comprises the recent share price history which is widely disseminated and readily available to the public, usually free of charge. In contrast, access to real time data on market quotes and transaction prices or historic databases must be paid for. Public information also comprises current financial information concerning profits, current capital structures or earning forecasts. Furthermore, it covers economic information about a firm's product market, competitors and national as well as international economic conditions or structural changes like recent innovations, acquisitions, divestitures, discoveries and regulatory changes. Private information includes information that individuals may possess because of their own investigations and analyses.

Each trader perceives changes in market prices as an integration of new information (historic, public, private) and compares them to his own individual expectation. Furthermore, if a trader disagrees with market prices he may change the price according to his own expectations. Hence, the price mechanism aggregates information comprised in market prices and thus market prices can be interpreted as a forecast because the aggregated information reflects all expectations from traders about the future development of stock prices (Forsythe et al. 1982; McKelvey and Page 1990; Forsythe et al. 1992; Plott 2000; Harris 2003; Schwartz et al. 2006). In price discovery processes, each rational market participant has reasons why he is going to buy or sell in a market. This information is reflected in market prices: if a market participant wants to sell, other participants recognize this as a signal that the valuation of that participant is lower than the actual price. Otherwise he would not put a sell order. As mentioned, orders and prices in markets comprise information interpreted by traders. They get information in newspapers, via the Internet or from their own experience. The "level" of information comprised in market prices can be described. Fama (1970) introduced the *efficient market hypothesis* which categorizes three levels of comprised information (Jensen 1978; Fama 1991):

- weak form of efficient market hypothesis
- semi-strong form of efficient market hypothesis
- strong form of efficient market hypothesis

The weak form of efficient market hypothesis states that all historic information is included in market prices. Historic information can be collected from records about stock prices, events in the past, e.g., political elections or sports events, or newspapers. It is assumed that all this information is reflected by market prices. The semi-strong form of efficient market hypothesis states that public information is instantly included in market prices. Information in news or press releases are available to every market participant and can be interpreted by them at once (Harris 2003; Schwartz et al. 2006). The strong form of efficient market hypothesis states that private information individually held by market participants is added to the weak and semi-strong form of efficient market hypothesis. To confirm the strong form of efficient market hypothesis, every individual information has to be included in the market prices, which cannot be assured for all individuals. Since the strong form of efficient market hypothesis cannot be confirmed due its strong assumptions (Jensen 1978), the semi-strong form of efficient market hypothesis is widely accepted. The semi-strong form of efficient market hypothesis is confirmed in various studies in finance and experimental markets (Smith 1982; Plott and Sunder 1988; Fama 1998; Jung and Shiller 2005; Markovitch et al. 2005).

3.1.2 Why Traders trade

Participants may have several motives to act in markets. Based on the market objective, one can classify between the aggregation of information to forecast future stock developments, risk hedging or speculation (Dietl et al. 2004). Besides the information aggregation objective, the investment of money in markets can also be a motive in order to earn interest. Harris (2003) distinguishes between *profit-motivated traders, utilitarian traders* and *futile traders*. Profit-motivated traders trade because they rationally expect to profit from their trades. Speculators and dealers are profit-motivated. Utilitarian traders trade because they expect to obtain some benefit from trading besides trading profits such as entertainment, gambling or fun. Investors, borrowers, asset exchangers, hedgers and gamblers are utilitarian traders. Futile traders believe that they are profit-orientated, but their expectations are not rational. On average, utilitarian and futile traders lose to profit-oriented traders (Harris 2003).

Investors put their money in stocks they think will raise and otherwise sell, if they assume that prices will decrease in the future. People with no information are called *Noise Traders* because they do not posses sound information about the fundamental value of stocks. In contrast, informed traders can exploit uninformed traders by using their superior knowledge and therefore, uninformed traders act as liquidity providers for informed traders (Glosten and Milgrom 1985; Das 2005; Boer-Sorban et al. 2007).

Traders normally underlie a so-called *self-selection* process. Since traders estimate the value of their own private information they decide to participate in a market or not. They have to evaluate the quality of their individual information against the information already included in market prices and finally decide, if they can make a profit in the market. Otherwise they should not participate in the market because they would be noise traders and lose money to informed traders on average (Harris 2003).

3.1.3 Engineering Markets

Today, the coordination of information via market mechanisms can be conducted using modern information technology (Malone et al. 1987; Weinhardt et al. 2003). Due to heavily decreasing transaction costs through the usage of information technology, electronic markets can be used for nearly any type of coordination. Electronic markets provide a cost efficient and scalable method facilitating the exchange of information, goods, services and payments (Bakos 1998). Smith (1982) argues for a complete description of the methodology and function of experiments in microeconomics and proposed a model for microstructure. Weinhardt et al. (2003) and Neumann (2004) proposed a framework for the coordination via markets considering the challenges and advantages of Information Technology and introducing a research direction named *Market Engineering*. The framework defines essential characteristics in order to design a market. Figure 3.1 shows the Market Engineering framework.

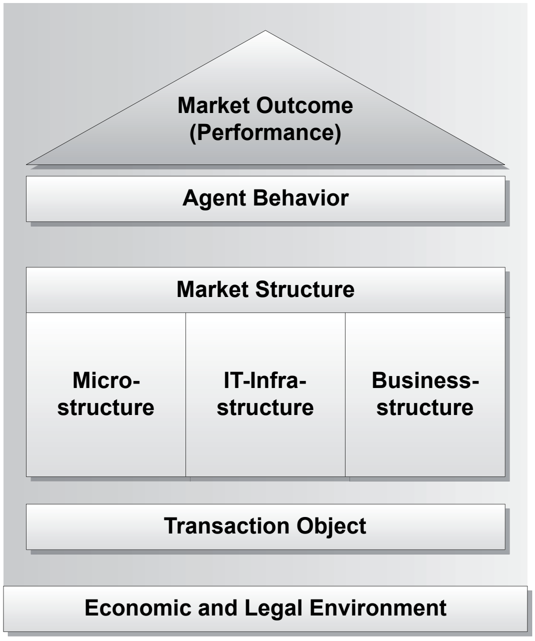


Figure 3.1: Market Engineering
Adapted from Weinhardt et al. (2003), Neumann (2004)

Regulatory aspects need to be considered in order to build a market system. Furthermore, the framework has to be embedded in the economic context of interest. The basic characteristic is the *transaction object*, which can be goods, stocks or services. To handle the transaction object, a *Market Structure* needs to be defined consisting of three properties: *Microstructure*, *IT-Infrastructure* and *Business Structure*. The Microstructure is about *how* the market rules are defined, which trading mechanism is used or, for instance, if traders may revoke an order. The IT-Infrastructure defines the information technology to be used for the Market Structure to operate, e.g., how a database interacts with the business logic and how market participants can put their orders into the system. The Business Structure defines how the Market Structure can be financed. For example, transaction costs can be charged for each transaction or market participants have to pay an entrance fee to join the market. Once the Market Structure is defined, market participants use the market and put their orders into the system. An agent does not need to be a person, it can also be an automated piece of software or a broker trading on behalf of another person. The behavior of agents is driven by the Market Structure. For example, trading fees, transaction costs, discounts or costs of additional information may influence agents' behavior (Weber 2006; van Dinther 2007). The performance of the Market Structure can be measured via the *Market Outcome*. Markets can, for example, be assessed by measuring their outcome, their liquidity or their efficiency. The latter answers questions such as: Did the agent with the highest valuation get the transaction object?

The overall framework provides a comprehensive guide to engineer markets because markets have to be engineered carefully due to the relation of Agent Behavior and Market Structure (Weinhardt et al. 2003; Neumann 2004; Weinhardt et al. 2006). A similar perception is reported by Roth: "market design calls for an engineering approach" (Roth 2002). Transactions in markets can be characterized by three distinguishable phases (Schmid 1993).

1. **Information Phase**
   Market participants inform themselves about offered products, prices or shipping costs.
2. **Negotiation/Agreement Phase**
   Market participants negotiate prices, guaranteeing, service features and finally come to an agreement.
3. **Clearing/Settlement Phase**
   In the Clearing Phase, goods are packed, insured for shipping, shipped by the seller and paid by the buyer.

These phases are representative for all transactions in markets. First, one has to inform oneself about the offers available in the market. After having all relevant information, market participants negotiate the price and other properties of the transaction object before the transaction can be cleared by paying the price and exchanging the good. These phases can be very complex and interminable depending on the type of transaction object.

Lindemann (2000) proposed a reference model for electronic markets adding different views to the transaction phases (Schmidt and Lindemann 1998). Figure 3.2 shows the model.

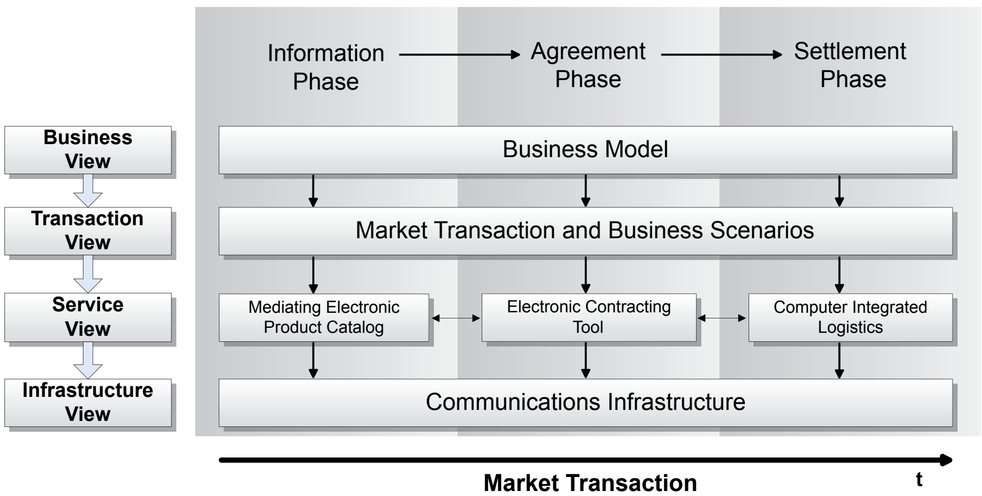


Figure 3.2: Electronic Markets Reference Model
Adapted from Lindemann (2000)

In every transaction phase, a view is implemented for, e.g., the communication with market participants, services to support contracting or logistics, transaction handling or the business model in order to align all components to add value along the transaction phases. Moreover, the trend towards electronic markets as well as Internet-based market research is clearly observable (Dahan and Hauser 2002b; Sawhney et al. 2005). Furthermore, experimental markets converge towards theory and confirm the expected theoretical results as well as the expected behavior (Forsythe et al. 1982; Plott and Sunder 1988; Forsythe et al. 1992).

As described, multiple parameters have to be considered in order to develop a market system. Each market has different requirements for its purpose and needs to be engineered carefully. In the next section, a special market type is introduced named "Information Market". After the introduction, market parameters for Information Markets will be discussed.

3.2 Information Markets

In recent years, a new way of using markets has come up by using market results to forecast future events named Prediction Markets or Information Markets utilizing the knowledge of many people or a community.[2] Information Markets are a special kind of markets that aggregate information held by people about uncertain events in the future. People are trading virtual contracts representing future events based on their individual expectation about the outcome of the events. Once an event has occurred, stocks held by people receive a payment based on the event.

The first usage of Prediction Markets can be traced back to 1868, when U.S. presidential elections were operated till 1940. Newspapers reported stock prices of candidates nearly on a daily basis. The betting activity sometimes showed more trading activity as the stock exchanges on Wall Street. Over the years, Information Markets were rediscovered in the late 1980's with the IOWA Electronic Markets for political forecasting (Forsythe et al. 1992). Roll (1984) reported that prices in orange juice futures can serve as predictor for weather changes. The usage of Information Markets is reported in different fields of application like sports (Servan-Schreiber et al. 2004; Luckner 2008), medicine (Polgreen et al. 2007), new product development (Soukhoroukova 2007), marketing research (Spann 2002) or entertainment (Pennock et al. 2001a). Even companies like Google, HP or Siemens use Information Markets internally to improve their decision making (Ortner 1997; Plott and Chen 2002; Cowgill et al. 2009). Several years later, after Surowiecki's book "The Wisdom of Crowds", Information Markets gained increased popularity in the public. In essence, the aggregation of individual opinions produces accurate and objective estimates (Lorge et al. 1958; Surowiecki 2004). In 2005, Information Markets (Prediction Markets) were firstly mentioned in the Gartner Hype Cycle of Emerging Technologies as technology trigger, which will reach the Plateau of Productivity after 2015 approximately (Fenn and Linden 2005). Figure 3.3 shows the Hype Cycle for Social Software as of August 2010. Information Markets are considered to reach the plateau of productivity in approximately 5-10 years. Thus, it is seen as a key technology for the future and offers a field of further investigation and research for the next years.

[2] In scientific literature, many equivalent names are used for Prediction Markets like Information Markets, Future Contracts, Fantasy Markets, Decision Markets, Idea Futures, Forecasting Markets, Artificial Markets, Electronic Markets and Virtual Stock Markets. In this work, Information Markets is used.

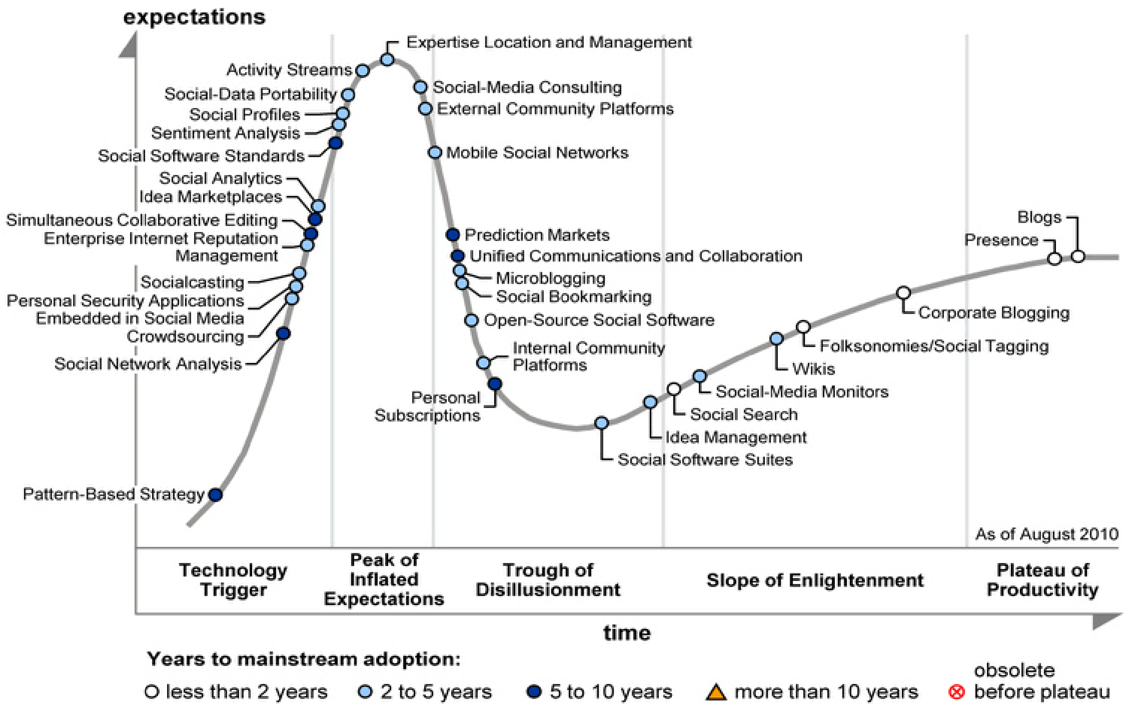


Figure 3.3: Information (Prediction) Markets in the Gartner Hype Cycle for Social Software

As a result of these developments, scientists have begun to investigate Information Markets (Tziralis and Tatsiopoulos 2007). Snowberg et al. (2007) and Wolfers and Zitzewitz (2009) interpret stock prices in political Information Markets as probabilities for a future event and connect their changes to changes in financial stock markets. In their results, they show a connection between political forecasts and economic variables. For example, if a republican president candidate is in favor for presidency, an effect in oil prices and equities is observable.

Moreover, Information Markets are highly scalable as they allow for an integration of a huge number of traders, whereas the effort to add an additional trader is negligible (Spann 2002). Dahan and Hauser (2002a) state that Information Markets are an efficient way of communication and interaction between traders. Traders can be integrated in early stages of forecasting objectives which is, for instance, essential in new product development or innovation assessment. Especially for decision makers in innovation contexts, a centrality in decision making reduces the exploratory innovation capability of companies (Jansen et al. 2006). Therefore, Information Markets can be utilized as decision support tool in order to decentralize decision making and utilize the collective knowledge of employees in decision making.

3.2.1 Terms and Definitions

Academia does not provide a universal definition of Information Markets. Tziralis and Tatsiopoulos (2007) conducted a review of academic literature regarding Information Markets. Figure 3.4 summarizes the types of publications classified.

As one can easily see, many terms are used in the academic literature for Information Markets. This shows the diversity of names used for Information Markets.

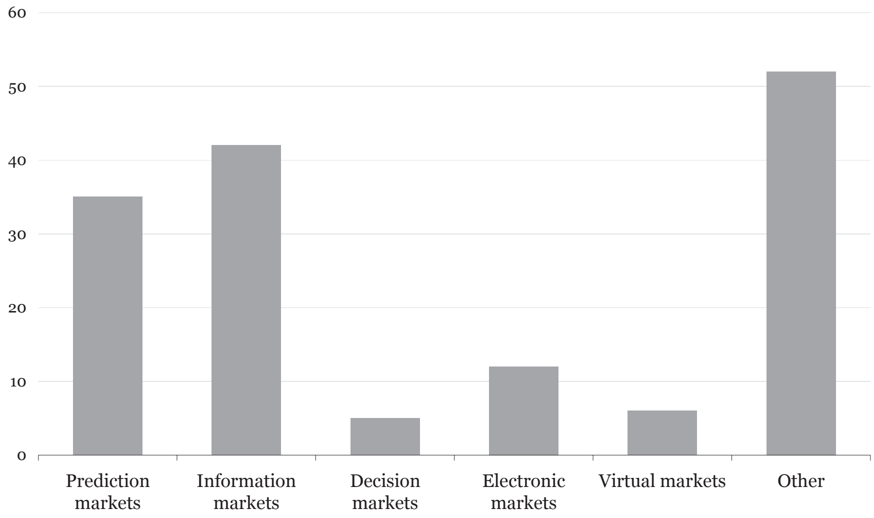


Figure 3.4: Academic Publications for Information Markets - Overview
Adapted from Tziralis and Tatsiopoulos (2007)

Since there is no universal definition available, Berg and Rietz (2003) formulated a definition of Information Markets, which is widely accepted in academic literature, for instance Tziralis and Tatsiopoulos (2007) or (Luckner 2008), and also used in this work. Following their definition Information Markets are run for "the primary purpose of using the information content in market values to make predictions about specific future events". In this work, an almost universal and exact definition of Information Markets is of minor importance. The essential meaning reflected in every reference to Information Markets is the aggregation of information via a market system.

In contrast to financial stock markets, Information Markets are not mainly designed to allocate resources, to trade risks or to make money. They are primarily designed to aggregate information in stock prices corresponding to the outcomes of future events (Tetlock and Hahn 2007). Information Markets are not substantial enough in size to trade risks or make money like financial markets (Wolfers and Zitzewitz 2004). Stocks in Information Markets rather represent an aggregation of trader's beliefs about future events, which do not have value by themselves. Once the future event has occurred, shares are paid out according to a payout rule, which differentiates them further from financial stock markets. In the following, the functionality of Information Markets will be described in more detail.

3.2.2 Functionality of Information Markets

Traders convey their information or expectation about future events through buying and selling virtual contracts in a market system. The market mechanism aggregates buy and sell offers whereas a transaction may occur if a buy offer overlaps a sell offer. The resulting transaction price determines the current market price for certain stocks. Market prices can be interpreted based on their value about how the likelihood of a future event is expected at the moment. Because of that, traders can update their expectations via repeated buy and sell actions, and they can affect market prices continuously once their expectation differs from market prices. If an equilibrium regarding market prices appears, it is assumed that traders have agreed to a consensus and trading activity will decrease till they update their expectations based on news or newly available information again (Fama 1970).

After the event in the future has occurred, the final value of stocks can be determined. Shares in traders' depots are paid out accordingly. Each trader has an incentive to maximize his portfolio value (Spann 2002). Furthermore, traders can be ranked based on their portfolio values and the top traders can be identified easily. A ranking of traders based on the portfolio value also includes a competitive and playful aspect.[3] Information Markets can be interpreted as "situational securities" and not as shares representing the value of a company because the payout value is linked to the outcome of an uncertain future event (Elton et al. 1995). If traders bought shares for less money than the final payout value, they realized a benefit. On the other side, if they sold shares for more money than the final payout value, they also made a profit. The following example will demonstrate the functionality of Information Markets.

Imagine that the executives of a home entertainment manufacturer need reliable information about the sales of high definition plasma TVs for the next quarter (Q3). They need the forecast of sales figures in order to plan their procurement strategy with respect to vendor parts. Therefore, they set up an Information Market and let their salesmen trade the sales figures for the next quarter (Q3). In the Information Market, shares representing the sales figures are available in intervals of 100, e.g., 0-100, 101-200, 201-300, and so on. As soon as the sales figures are known, stocks representing the correct interval are paid out of the share at 100 $. For example, if the market price of the share "401-500 sales in Q3" at a certain point in time is 85 $, the aggregated forecast of all participating salesmen is 85 % that the sales figures will be 401-500 units. Thus, a stock price of 85 $can be interpreted as a likelihood of 85 % that sales will be 401-500. If traders do not agree and think that the probability of sales will only be 60 %, they have to sell shares from their depot. If they think the likelihood is 90 %, they have to buy shares in the market in order to raise the price. In that case, rational traders would buy shares up to 89.9 $and sell shares down to 90.1 $, respectively. Figure 3.5 illustrates the functionality.

In the following, the process will be explained briefly: Each salesman has direct contact to customers and has experience concerning their needs and preferences about high definition plasma TVs. Salesmen integrate their information via buy and sell offers ❶. The market mechanism immediately aggregates all expectations reflected in buy and sell offers. Based on the market mechanism, incoming offers are processed once they enter the market system. Already accepted orders are executed in case of corresponding incoming buy or sell orders. As a result, a new transaction price is calculated which reflects the aggregated information. If an offer matches several others, all matching offers are executed if the volume of the incoming offer exceeds the cumulative volume of overlapping offers listed in the order book. Otherwise, offers will be partly executed. The higher a trader considers the likelihood of the event, the higher his reluctance to sell will be. Therefore, stock prices represent the collective estimation of participating traders about a future

[3] Incentive schemes will be described in Section 3.3.3.

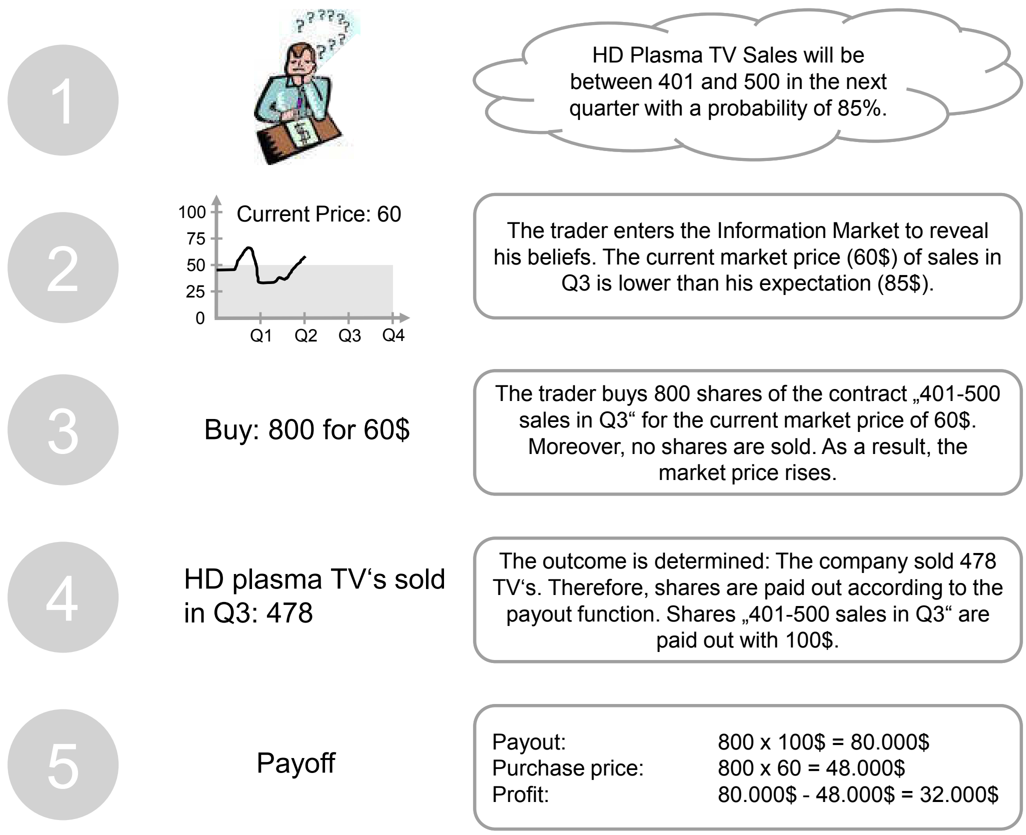


Figure 3.5: Functionality of Information Markets

event ❷. Through buying and selling shares, traders can win or lose (virtual) money. In the example, the salesman buys 800 shares at 60 $ ❸. If the final value in the above mentioned example of TV sales is between 401 and 500, the corresponding share will be paid out with 100 $ ❹. The salesman realized a profit in this case. He bought undervalued shares which were paid out for a higher price ❺.

Information Markets motivate traders to reveal their beliefs and not their preferences (Forsythe et al. 1992; Spann and Skiera 2004). Shares are paid out according to the outcome of a future event and trading according to preferences would lead to monetary losses if the individual preferences did not relate to the outcome of events. Even an enthusiastic salesman should not trade his preferences and maybe boost sales forecasts because he could lose money in case of overestimating the true numbers. The monetary incentive schema in Information Markets is therefore very well suited to motivate traders, because it is performance-based. The better traders act in markets by truly revealing their beliefs, the more money they can make. While every trader reveals his beliefs, the market mechanism is a comfortable mechanism to aggregate all these beliefs continuously and update the forecast of uncertain future events permanently.

3.3 Designing Information Markets

As mentioned in Section 3.1, the careful design of markets is essential for the success of its result (Weinhardt et al. 2003; Weinhardt et al. 2006). An elaborated user interface is also necessary in order to guarantee a satisfying user experience in Information Markets. Moreover, compared to financial markets, other challenges like incentives or contract design exist and have a different impact on the market result. If the contract design is not appropriate, traders may misinterpret the contracts's intended purpose and, thus, results may be off target. Moreover, inaccurate incentive schemes may not foster traders to trade constantly. In financial markets, for example, users usually trade values of companies and have precise motives why they do so, e.g., bonuses or rate of return (Harris 2003). In Information Markets, incentives have to be set in order to keep traders in the market. Most Information Markets use virtual money instead of real money, because real money investment representing future events may cause legal issues in some countries. Traders have to be incentivized throughout the whole market duration, which may last weeks, months or even years. Furthermore, the specification of contracts as well as the trading mechanism has to be defined (Spann and Skiera 2003). For instance, contracts can be designed to forecast index values, which can be interpreted as likelihoods of events. In contrast, they can be designed to forecast outcomes of events with so-called "winner-takes-all" contracts (cp. Section 3.3.2). Another key design issue is the selection of traders, which should be heterogeneous, and the availability of information to ensure that traders have a foundation to develop expectations to reveal them in Information Markets (Spann and Skiera 2003; Wolfers and Zitzewitz 2004; Tziralis and Tatsiopoulos 2007). The overall challenge in Information Markets, and also in every other market system is liquidity and information efficiency. Low liquidity markets may hinder traders to trade once they do not have a counterpart to trade with. As a consequence, information cannot be integrated and therefore a market cannot be information efficient. Market liquidity and efficiency as major challenges in Information Markets will be further discussed in Section 3.3.4.

From the technical point of view, an appropriate Information Market Web System has to be implemented in order to provide the functionalities to participants conveniently. As mentioned by Schmid (1993) and Weinhardt et al. (2003), the IT infrastructure is of utmost importance. In the following sections, the key design elements of Information Markets are described in more detail.

3.3.1 Traders

The number of traders in Information Markets varies depending in the objectives of the Information Market. Different factors of influence are affecting the number of traders: the type of contracts, incentive mechanisms, the runtime of the market or the amount of traders (Sunder 1995). Nevertheless, markets can produce proper results in enterprise forecasting topics with only 12 traders whereas on the HSX[4] several thousand traders are active (Spann 2002). One might assume that the traders should represent the population, however Information Markets do also show accurate results if traders are not necessarily representative. But, there have to be some traders with strong preferences (Forsythe et al. 1999; Spann and Skiera 2003).

Information Markets yield very good results if some traders make "mistakes" in estimating the likelihood of future events. Informed traders exploit the mistakes of

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

others and do therefore improve the current forecast (Forsythe et al. 1999; Oliven and Rietz 2004). Forsythe et al. (1999) classify informed traders as “marginal traders”. In a laboratory experiment about forthcoming presidential elections they identified 20 out of 192 traders as marginal traders.

In general, traders try to utilize their personal knowledge to determine the value of stocks (Lucas Jr. 1972). This principle is well established in real world markets as well as in experimental markets, where traders have an incentive to reveal their true beliefs about an event (Plott and Sunder 1982; Smith 1982). These beliefs are developed through the analysis of historic price evolutions or the interpretation of events such as news in newspapers, TV or the Internet. Traders develop their individual expectation about the likelihood of events. As aforementioned, market prices in Information Markets also carry information. Traders with strong preferences can lead the majority of traders which are going to follow. Traders continuously update and reassess their beliefs (Blanchard and Watson 1982; Timmermann 1993). Therefore, it may happen that traders show a herding behavior and cause bubbles or crashes (Smith et al. 1988). Traders exposed to other traders’ preferences may change their expectations and beliefs dramatically (Salganik et al. 2006). Hence, it is important to ensure that traders get enough information about the objective of the market so that they can build their own beliefs based on news events. If market prices of other traders are the only information, herding behavior is likely, which may lead to inaccurate market prices or market failure in the worst case.

During the market runtime, a trader analysis can be conducted in order to identify so-called *Lead Users*. Lead users are very successful traders interpreting news precisely (von Hippel 1994; Lilien et al. 2002; Spann et al. 2005). Information Markets have the advantage that, in contrast to financial stock markets, the trading data of individual users is available. In financial markets, individual traders are anonymous or trade via brokering systems, whereas the information about which trader did what kind of trade is usually not available to analysts. Lead users are favorable as a valuable source in Information Markets (von Hippel 2005). Once they are discovered, ongoing steps are possible such as interviews about how they came to their expectations and beliefs. This may be valuable, for instance, in innovation assessment tasks where decisions are linked to very expensive and costly follow up processes. Decision makers can use an Information Market to identify employees interested in their main topics in order to reward them or invite them for further assessments and forecasts. Lead users can be identified based on their trading direction. If a trader buys an undervalued or sells an overvalued stock, the trading direction can be analyzed if the trade was *right* or *wrong*. This analysis can only be conducted ex post once the final value is determined. Otherwise one cannot assess the trading direction because the final value is needed to decide which trade was right and which one was wrong. In addition, the ranking of traders based on the portfolio value gives an indication of trader’s performance. The ranking is continuously updated and works even during the market runtime.

In enterprise contexts, one cannot only rely on employees in complex forecasting topics. In those cases, the involvement of suppliers, consultants, customers and researchers can be beneficial (Alam 2003; Majchrzak et al. 2004; Emden et al. 2006). In order to get an objective assessment as well as to widen the base of valuable expectations and insights, the involvement of external people and partners is to be considered in setting up an Information Market. As mentioned in Section 2.1.5, externals are a valuable source for innovation in terms of Open Innovation. Information Markets as a web-based application allow the easy integration of externals via authorization procedures. Therefore, even externals from cooperating companies can access markets for certain topics from the outside and provide their information.

3.3.2 Types of Contracts

In Information Markets, the type of contract can vary based on the forecast objectives. In order to forecast sales figures, for example, one can forecast an absolute value of sales or an interval in which the outcome is expected to lie. It is of utmost importance that contracts are intuitive and easily understandable so that traders can easily understand what they are supposed to do. Contracts can be differentiated in *winner-takes-all*, *index* or *spread* contracts (Wolfers and Zitzewitz 2004).

In case of a winner-takes-all contract, only the winning contract will be paid out according to the payout rule. All other contracts expire and are not paid out. This type of contract is mainly used to forecast one out of several alternatives, e.g., the winner of a soccer tournament. All prices in winner-takes-all contracts have to sum up to equal the sum of all payouts. For example, if a soccer team wins a championship and only the representing contract is paid out at 100 currency units, prices have to balance over all contracts. Once the total sum of all contracts exceeds the total sum of the payouts, arbitrage trading is possible. Shares can be bought from the Information Market operator and sold to the market and vice versa. Thus, efficient markets should show an equal sum of payments and stock prices. Summarizing, prices can be interpreted as aggregated expectations about the probability of a future event, e.g., a soccer team winning the tournament (Wolfers and Zitzewitz 2006).

Index contracts are used to forecast an event with a direct number. For example, the percentage of a candidate in a political election. The payout function in this case is linked to the final value. If a candidate receives 70 % vote share, the contract will pay out 70 currency units. Market prices of index contracts can be interpreted as mean values aggregated from traders.

Spread contracts pay out if the number of votes a candidate receive exceeds a pre-defined threshold, otherwise the contract does not pay out. Hence, the spread contract reveals the market's median expectation if contracts are designed in a way that winners double their money and losers do not get any payment.

In addition, one can create other contract types with very sophisticated functionalities. Yet, the intuitiveness and simplicity for traders should be regarded in order to keep it simple to understand. Another difficulty is the continuity of contracts. It may be the case that in a political election one candidate revokes his application during the election campaign. As a consequence, the outcome of the event may be distorted as the results become non-verifiable. Such eventualities must be carefully considered in the market design.

3.3.3 Incentive Schemes

In Information Markets, traders are revealing their beliefs and expectations about future events via buying and selling stocks representing future events. Their effort is usually compensated once the market closes. Shares are paid out according to the outcome of the event (Spann and Skiera 2004). As mentioned in Section 3.2.1, traders have the incentive to reveal their true knowledge (Plott and Sunder 1982; Smith 1982; Spann and Skiera 2003; Wolfers and Zitzewitz 2004; van Bruggen et al. 2006). In contrast, the better a trader anticipates the outcome of an event, the better he will perform in the Information Market. In contrast to a survey, traders are compensated based on their performance. In a survey, the performance of each participants is usually not causal for any reward. Hence, the incentives for traders Information Markets is different from other methods of information aggregation.

The incentive system can be designed in different ways. Scientific literature suggests, that contracts in Information Markets pay real money or virtual money[5] as a very common to be used in incentive systems (Servan-Schreiber et al. 2004). Smith and Walker (1993) investigated that increased monetary incentives bring traders' behavior closer to predictions of economic theory. Rosenbloom and Notz (2006) found that real-money markets are more accurate for non sports events. Servan-Schreiber et al. (2004) found out, that there is no difference observable in sports events regarding real money and play money markets.

In general, different motives can be utilized to serve as incentives for traders. Motzek (2007) and Lakhani and Panetta (2007) describe three types of motivations why people are incentivized in doing something.

1. **Intrinsic Motives**
   People do something because it is perceived as inherently interesting and pleasant. Therefore, an activity may be performed for the fun of it or because for immediate satisfaction, the need for fun, notions of enjoyment and entertainment.

2. **Extrinsic Motives**
   Activities with extrinsic motives do not deliver satisfaction until the assignment is accomplished. The objective is to complete a task because of the compensation or sanction attached. People expecting extrinsic rewards can, in terms of productivity, outperform those who do not receive a reward. Often, a monetary compensation is used as extrinsic incentive.

3. **Social Motives**
   Individual behavior is influenced by others and may complement the first two classes of motives (intrinsic and extrinsic). This is especially true in groups or communities in which a person's behavior is visible to others. Social motives include community affiliation, reputation and feedback from others for the own achievements.

In Information Markets, components of all three types of motivation are exploited. Firstly, it is assumed that traders in Information Markets enjoy using the market

[5] In this case, virtual money profits can be redeemed to in-kind prices.

system and that trading itself is perceived as interesting and entertaining. Especially in sports markets, where the public interest is high, joy and entertainment is a leading factor, for instance, if one's preferred soccer team traded is included somehow in the Information Market. This may lead to favorite long-shot biases[6] as reported by Luckner (2008). In other fields of application, fun and entertainment are also an intrinsic factor for people to participate in Information Markets. Secondly, prizes are raffled as an extrinsic motivation for participants, usually based on the individual performance of each participant. Prizes can be both monetary and non-monetary. Motzek (2007) states that extrinsic motives can also serve as a catalyst for intrinsic ones. For example, if a task assigned begins to be entertaining and raises interest or if money is awarded as extrinsic incentive and collecting money is an intrinsic motive. Thirdly, social motives are exploited via the competition of traders. The performance of traders is visible in a ranking of all participants. Thus, the success and failure in trading activity is visible to all market participants and may serve as an incentive for traders. Participants perceive a high rank as satisfaction at their achievements and reputation among other trader. Combined with fun, entertainment as intrinsic motives and prizes or other types of extrinsic incentives, Information Markets can make use of all three types of motives to attract participants.

Besides the listing in a ranking based on the depot value, other ways of measuring the performance of traders are imaginable. In a recent field experiment about the forecasting of economic variables named EIX[7], a scoring function was implemented measuring traders success based on their trading direction (Teschner et al. 2011). As mentioned in Section 3.3.1, the trading direction represents the fraction of "right" transactions as a partition of the total number of transactions. In case of the EIX, the number of transactions is multiplied with the percentage of "right" transactions to get the score. Furthermore, traders can win several main prizes after the market duration based on the portfolio value. In order to not put traders registering to the market after other traders begun to raise their depot value at a disadvantage, monthly prizes are raffled based on the monthly performance regardless of the overall depot value. Hence, traders have an incentive to perform well every month. Traders have to fulfill two constraints. They have to increase their portfolio value compared to the last month and they have to conduct at least five transactions.

The field experiments described in Chapter 4 uses a ranking system with a winning probability. The winning probability represents the fraction they have in the total sum of traders' portfolios. All portfolios are standardized and every traders portfolio is described by the fraction of the total sum. The winning probability is metered as a fraction of the total sum of all depots in %. After the market closes, the prize is awarded under all traders based on their winning probability. A trader with a high probability had a higher chance to win the prize. This design is chosen also to incentivize traders who enter the market after it has started. Otherwise, traders who have joined the market in the very beginning would have an advantage, benefiting from former trading activities. In Section 4.1.3, the concept will be described in more detail.

[6] Traders overestimate high likelihoods and underestimate low likelihoods.

[7] Economic Indicators Exchange, http://eix-market.de, accessed 15.04.2010

3.3.4 Market Liquidity and Efficiency

Adequate market liquidity is essential for the information aggregation process (Harris 2003; Schwartz et al. 2006). If a market suffers from illiquidity, efficient aggregation cannot be guaranteed and, therefore, market failure is foreseeable (Glosten and Milgrom 1985). Information Markets proved to be operational with 8-12 active traders (Spann 2002; Soukhoroukova 2007). Thus, several more traders are necessary to create minimum liquidity that 8-12 traders can efficiently trade since not every trader is active to the same level. In a CDA mechanism, traders reveal their beliefs about future events via buy and sell orders. As a prerequisite, each trader needs to have a counterpart so that a transaction can occur for matching orders. If only a few traders are in the market, trading activity may be extremely low and, therefore, the information aggregation mechanism cannot work properly. In scientific literature, several reports exist about the liquidity in (Information) Markets investigating the effect on information efficiency.

In general, liquidity in markets is often discussed but rarely well understood (Harris 2003). In scientific literature, liquidity has several dimensions: Immediacy, Width, Depth and Resiliency (Harris 2003). Immediacy is the ability to trade quickly at given costs. Width refers to the cost of doing a trade, which is often identified by bid/ask spreads[8]. Depth refers to the size of a trade at a given cost and is measured in units of shares available. Resiliency refers to how quickly market prices revert to former levels after a distortion of prices initiated by uninformed traders. Therefore, liquidity can be described via different measures in each dimension. In this work, mainly measures regarding width and immediacy are used to describe the liquidity of markets in Sections 4.4 and 5.3.

As mentioned in Section 3.1.1, efficiency in markets is defined as the ability of markets to integrate information. New information about companies, technologies and trends is interpreted by traders and is represented by their trading strategies in stock markets. In frictionless, optimal markets, stock prices follow a random walk pattern which means, that it is indeterministic if the next trade will be a buy or sell (Schwartz et al. 2006). This can be measured with the first order auto-correlation. In perfect markets, the auto-correlation coefficient is 0. In typical stock markets, a coefficient of 0.4 is often observable, which means that sell offers follow on sell offers more often than buy offers follow on buy offers. Furthermore, efficiency can be expressed with arbitrage opportunities. If large arbitrage opportunities are available, markets did not integrate available information efficiently, because traders can buy shares in one market and can sell them at a higher price in another market, if the market rules allows that. Thereby, they realize a riskless profit. If both markets are efficient, such transaction does not offer the opportunity to realize profits (Schwartz et al. 2006).

Tetlock (2008) investigated three years of TradeSports[9] trading records. TradeSports was a real money Information Market to forecast mainly sports events.[10]

[8]Bid/Ask spreads are the difference of the lowest offer to sell (Ask) and the highest offer to buy (Bid) shares.

[9]http://tradesports.com, ceased operation in 2008

[10]In 2003-2006, 70 % were sports events, 25 % were financial events and about 5 % were other events like economic, political, entertainment, legal or weather and micellaneous.

Analyzing data from 2003-2006, Tetlock reports that "liquidity does not reduce deviations of prices from financial and sporting event outcomes". Tetlock argues that excessive liquidity spending mechanisms encourage informed traders to make short term speculation. On the other hand, liquidity offers traders a chance to reveal their private information.

Anand et al. (2005) investigated the evolution of liquidity in NYSE stocks. They conclude that informed traders buy early and sell shares later once they disagree with the stock price. This kind of liquidity supports the assumption that liquidity fosters market accuracy. In addition, Wurgler and Zhuravskaya (2002) report that the risk of arbitrage trading is higher for smaller stocks. This effect occurs whenever the liquidity available in markets does not suffice to exploit arbitrage opportunities. This may also harm stock price efficiency in illiquid markets. Chordia et al. (2008) report that, based on their investigation on market liquidity and efficiency, liquidity facilitates efficiency. Moreover, they suggest that volatility induced by private information during trading hours increases along with liquidity. This is a strong evidence for the necessity to have appropriate liquidity in markets in order to support an environment in which traders have the possibility to reveal their private information and are not restrained from trading activity due to missing counterparts. Bloomfield et al. (2009) analyzed informed and uninformed traders' behavior in a laboratory experiment and found that even taxes on transactions did not have a severe influence on the result: taxes only caused a small decrease in trading activity. However, the appearance of uninformed traders had a positive effect on market liquidity, whereas volume and depths were higher and spreads were lower.

All these examples show that the impact of liquidity is different depending on the market objective, the domain of application and the type of data itself. In general, one cannot develop a general market design that fits for every market application (Weinhardt et al. 2003). Especially in Information Markets in innovation contexts, the role of liquidity is of utmost importance because traders are in most cases employees in enterprises assessing innovation alternatives. Employees do not have plenty of time to reveal their beliefs and expectations in Enterprise Information Markets (EIM). Once they like to reveal their information, the market must be capable of providing them a chance to act. Otherwise, valuable information will get lost.

In Chapter 4, a field experiment will be described which investigates the impact of automated market making as an approach to foster liquidity and therefore forecast accuracy in Information Markets. The effect of (automated) market making in markets was already researched by several researchers. In the following section, different methods of market making will be described.

3.3.4.1 Market Maker Mechanisms

In order to avoid extremely illiquid markets, researchers recognized the necessity to provide a market maker mechanism in markets. Nearly every considerable Information Market employs automated market maker mechanisms in order to provide additional liquidity. For example, the Hollywood Stock Exchange (HSX), the Washington Stock Exchange (WSX), Inkling Markets and several others rely on automated market makers.

A commonly used method named Market Scoring Rule (MSR) was introduced by Hanson (2003). Hanson developed the MSR as an automated mechanism to provide liquidity in Information Markets. Market Scoring Rules are like two-sided market[11] makers providing unlimited liquidity for the sell side of the market. The market risk of the market operator is bounded which can be seen as a subsidy for the market. A MSR works substantially different than a CDA. A MSR maintains a probability distribution for all events and traders can buy or sell shares if they like to change the current probability for an event. Market scoring rules can be seen as a sequentially used proper scoring rule where information is integrated immediately. If traders move market prices in the right direction, they can expect a positive payoff, otherwise they will lose money. In exchanges like Inkling Markets[12] or the former Washington Stock Exchange[13], the MSR is implemented. One major challenge is the setup for agility and reactivity. The behavior of the price setting mechanism inside the MSR is steered by a certain factor. If the factor is defined to low, the MSR reacts sedate and to volatile otherwise. Therefore, finding the right setup is difficult because the behavior of the MSR needs to adapt to the current level of liquidity in the market. Another problem is the transparency to traders. It is a valuable information for traders if one side of the order book is filled with orders whereas the other side is nearly empty. Hence, one can interpret that the majority of traders expect a movement of market prices. In contrast to the CDA, where open orders are shown in an order book, the MSR has no capability to maintain open orders. Therefore, valuable information is not accessible by traders as it would be in case of the CDA.

Another market making mechanism is the Dynamic Parimutuel Market (DPM) which employs concepts from the CDA and parimutuel markets. Parimutuel markets are commonly used in horse race betting. They collect monetary bets from bettors and keep them in a central pool. The money is divided among the winners. Therefore, this infinite liquidity avoids the problem of illiquidity completely. On the other side, bettors have no incentives to reveal their beliefs early. They can observe how other bettors place their bets and react to them. Information cannot be integrated immediately and the market does not consolidate the beliefs of all bettors at once. Pennock (2004) developed the DPM mechanism to overcome this problem by combining the infinite liquidity of parimutuel markets and market mechanisms reflecting traders' beliefs continuously. The mechanism offers to buy in liquidity and acts as a one-sided market maker only offering to sell at some price in order to move the market price according to demand. One-sided market makers do not accept sell offers and therefore traders can sell their shares via a CDA mechanism, allowing them to limit their losses. The market operator is not exposed to risk in the DPM, because money is redistributed in the market and he needs not to put money into the market to keep it liquid. Via the CDA mechanism, traders can "hedge-sell" by buying the opposite outcome (Pennock 2004). The DPM is implemented in the Tech Buzz Game[14] operated by Yahoo (Mangold et al. 2005). A similar challenge, as mentioned before, is the order transparency. In the DPM, traders cannot com-

[11] A two-sided market allows offers on the sell as well as on the buy side in parallel.
[12] http://inklingmarkets.com
[13] http://thewsx.com, now managed by Consensus Point
[14] http://buzz.research.yahoo.com

Table 3.1: Trading Mechanisms Comparison

	CDA	MSR	DPM
Guaranteed Liquidity	○	●	◐[a]
Continuous information processing	●	●	●
Risk for operator	○	◐[b]	○
Transparency	●	○	◐

● satisfied, ◐ partly satisfied, ○ not satisfied

[a] Guaranteed liquidity on the buy side, but not on the sell side.

[b] Operators' risk is bounded.

municate that they are willing to trade at another price as quoted by the DPM mechanism.

In Table 3.1, the introduced mechanisms for market making in Information Markets are compared.

The described mechanisms were mainly used in Information Markets. In financial literature, several approaches and research directions exist for automated market making, which are also relevant for Information Markets. Due to the flexibility of the market mechanism and the order transparency to traders, the CDA was chosen to be implemented in the field experiment which are introduced in Chapters 4 and 5. Therefore, four approaches for market making strategies in CDA market mechanisms will be briefly introduced in the following section.

3.3.4.2 Market Maker Mechanisms for CDA

In the following, four approaches for market making in CDA markets are briefly introduced.

- Glosten and Milgrom (1985)
  The authors proposed a model to compute bid and ask orders based on order flows from informed as well as uninformed traders. They assume that the market maker earns zero expected profits on each purchase and each sale and faces no transaction costs. The model computes bid and ask prices based on the probabilities that the next order will be a buy or sell order respectively.
- Shelton (2001) introduced a learning market maker model which uses a learning algorithm for software agents acting as market makers. Those agents have a set of actions as well as a set of observations. Actions may be lowering or widening the spread as well as adjusting the volume of orders. Observations are the "imbalance" of buy and sell orders which will result in an appropriate action. Based on the expected profit, the learning algorithm learns and adapts these actions from past trades and chooses the action which is assumed to maximize profit in future market situations.
- Das (2005)
  Das picked up Glosten and Milgrom's model and enhanced it. The market maker tracks a density function about the true value of stocks whereby the market maker tries to learn that value in order to set appropriate bid and ask orders. The model considers the appearance of informed, noisy informed as

well as uninformed traders. Furthermore, Das' model considers market makers profits and provides inventory control.

- Boer-Sorban et al. (2007)
  Boer et al. applied a model to overcome the shortcomings (discrete time slots per sequential trader) in Das' model by extending it to a continuous model. The authors ran several simulations and showed that the market maker can learn the fundamental value of stocks passably well in different scenarios.

While all described models are promising approaches contributing to the common understanding of the dynamics of markets, all have shortcomings with respect to their usage in real world scenarios. For example, the models of Glosten and Milgrom (1985), Das (2005), Boer-Sorban et al. (2007) use algorithms which are very useful to learn the fundamental value of stocks by tracking the traders' order flow. To maintain a density function about the fundamental value, the market maker needs to know about traders' orders. Even if a trader does not want to trade, the market maker needs to know it in order to update the density function. Furthermore, the fundamental value must be well defined which is very difficult in service innovation scenarios. Markets with both perfectly informed and noisily informed traders are not considered either. Glosten and Milgrom (1985) do not consider market makers profits whereas Das (2005) abandons a continuous market and proposes a market organized with bidding rounds which is similar to a CA. Also, each model, except the market scoring rule, maintains investors' planning of only one step ahead, which is unrealistic because traders are usually planning more than one step. The models from Glosten and Milgrom (1985), Das (2005) and Boer-Sorban et al. (2007) assume that the market maker knows the fraction of informed/uninformed traders in the market, which cannot be maintained. The approach by Shelton (2001) uses a simple model of automated market making where traders are not allowed to trade against each other. They were only allowed to trade with the market maker. Furthermore, all positions were liquidated at the end of the trading day in order to limit the risk for the market maker.

As mentioned, no optimal solution for automated market making can be found in scientific literature for the application in Information Markets operating 24 hours, 7 days a week. Moreover, each Information Market requires different customized mechanisms related to the market objectives as well as the appropriate market design. In Chapter 4, a field experiment will be described in which an automated market maker agent as a piece of software was developed for that experiment using simple strategies. In contrast to the MSR and the DPM, a CDA mechanism was implemented for the experiment since an open order book can be provided which carries information which are not available in the MSR or the DPM.

3.4 Fields of Application

Over the years, many Information Market experiments have been conducted to forecast events in different fields of application. But not only experiments were reported in scientific literature, also theoretical and descriptive work has been published. Tziralis and Tatsiopoulos (2007) conducted an extended literature review and classified existing Information Market literature. They classified 152 research papers and counted 72 articles as application reports. Descriptive and theoretical work sum up to 60 articles whereas reports about law and policy sum up to 20 articles. The majority is, therefore, about applications in the field.

3.4.1 Politics

As mentioned in Section 3.2, early introductory articles by Hanson (1990a), Hanson (1990b), Hanson (1992) were followed by the majority of articles about political stock markets. The IOWA Electronic Markets (IEM)[15] started forecasting political elections and was operated by the University of Iowa. The first scientific report about the IEM was published in 1992 (Forsythe et al. 1992). The IEM focused on US presidential and state elections. The platform was also used to forecast presidential elections in Austria, Korea, France as well as Germany. Stock Prices in Information Markets react very quickly to new information because traders reveal their information at an early stage of the market, especially in markets of high public interest (Berg and Rietz 2006). In recent years, the IEM has not only focused on political events, but also allows the trading of economic indicators.

Further political stock markets were conducted in Canada (Antweiler and Ross 1998), Sweden (Bohm and Sonnegard 1999), Germany (Beckmann and Werding 1996) and Austria (Ortner et al. 1995), where they regularly outperform traditional polls (Berg et al. 2000). Due to this outstanding success, political stock markets have gained a lot of attention in the media. Agencies and publishing houses even started to operate their own political stock markets (Filzmaier et al. 2003).

3.4.2 Sports

The prediction of sport events is very popular in markets like Betfair.com[16], World Sports Exchange[17] or NewsFutures[18]. Popular sports events cover Baseball, Basketball, Hockey, Football, Golf, Tennis, Boxing, Soccer, Horse and Auto Racing. NewsFutures runs a general approach not limited to sports events. They provide even political betting, financial markets or movie stocks. Like political markets, sports markets are often at least as accurate as experts' forecasts (Servan-Schreiber et al. 2004; Chen et al. 2005; Tetlock 2006). The first Information Market about soccer matches was introduced by Schmidt and Werwatz (2002). Luckner (2008) operated another Information Market during the FIFA Soccer World Championship in 2006 forecasting the world soccer champion. Moreover, Information Markets for sports events react very quickly according to the efficient market hypothesis. It is reported that horse race betting markets in the UK fulfill the weak as well as the strong form of market efficiency (Smith et al. 2006; Luckner 2008).

In order to seize the full potential of Information Markets, appropriate incentives have to be designed for participation and information revelation (cp. Section 3.3.3). Therefore, Information Markets like Betfair.com or the IEM require real money investments from traders. As further stated in Section 3.3.3, several reports investigated the effect of real money vs. play money in sport Information Markets.

[15] http://www.biz.uiowa.edu/iem
[16] http://www.betfair.com
[17] http://www.wsex.com
[18] http://www.newsfutures.com

The results show that there is no significant difference between real money and play money markets (Servan-Schreiber et al. 2004). In general, these results are contrary to those from Rosenbloom and Notz (2006) whose work indicates that no final answer can be made to the question of accuracy between play money and real money markets.

3.4.3 Enterprise Information Markets

Information Markets in enterprises were firstly introduced to forecast software development projects (Ortner 1997; Ortner 1998). Based thereupon, many enterprises used Information Markets for different kinds of forecasting applications internally (Surowiecki 2004). One of the main objectives of using Information Markets is the exploitation of performance-based incentive system as an effective way to motivate employees (Griffiths-Hemans and Grover 2006). The remuneration of employees based on their individual performance in Information Markets is dominant in contrast to the incentives in traditional surveys, which are not performance-based. Surveys do not have motivational aspects like competition with colleagues, playful aspects, performance-based incentive mechanisms or a continuity of information aggregation. Therefore, companies have been experimenting with Information Markets in order to enrich their decision making by involving employees.

Siemens tried to forecast software development projects with Information Markets. Ortner (1997) and Ortner (1998) set up several markets investigating how accurate the forecasts were. The results show that participants anticipated new information, rumors and personal feelings long before official statements were published. In an enterprise-wide experiment, Google also used Information Markets to forecast whether a project would be completed on time or whether a particular office would be opened (Cowgill et al. 2009). A very traditional decision making forecast was conducted at Hewlett-Packard, aiming at the forecast of sales figures of printers (Plott and Chen 2002). Their results show that the market beat the official HP forecasts regularly. An internal Information Market at Eli Lilly aimed at finding out which drugs are the most successful ones (Kiviat 2004). 50 employees at Ely Lilly involved in drug development – chemists, biologists, project managers – traded six mock drug candidates through an internal market and predicted the three most successful drugs. British Petroleum (BP) also experimented with Information Markets to forecast different sales scenarios.[19] At BP, the market mechanism generated a prediction that was significantly closer to the actual sales than the traditional sales forecast.

Recently, the usage of Information Markets has been extended to the assessment of new product alternatives (Soukhoroukova 2007; Chen et al. 2010). Such an innovation context yields a special challenge since the final value of the shares traded cannot be used for the payout of stocks. In order to determine which innovation alternative is the most promising one, all alternatives have to be evaluated. Due to unreasonable costs, enterprises cannot implement all alternatives and thus, must decide which one to implement. Up to now, several methods and tools were introduced to support decision making in innovation contexts, but there is no general

[19] http://www.accenture.com/NR/rdonlyres/0DEC6700-DAB1-41BF-942E-FC8C2F61EDFF/0/know_markets.pdf, accessed 23.04.2010

rule to guarantee success. Information Markets are considered as an additional decision support tool to involve employees into the assessment of innovation alternatives. Information Markets provide some advantages over traditional methods in order to integrate employees such as the convenient analysis of results or the usage of incentive mechanisms, Thus, Information Markets are a powerful method to assess innovation alternatives continuously. For the market operator, it is also convenient. The results are not to be evaluated or aggregated because the market mechanism provides a continuous indication and aggregation mechanism, with which intermediate results can be assessed continuously.

Due to the fact that no final value of the innovation alternatives can be observed, the objective of an Enterprise Information Market (EIM) for innovation assessment is to aggregate information from employees rather than forecasting an event. Therefore, the market design has to be engineered more carefully in order to allocate the right incentives for participants. Nevertheless, Information Markets for new product development have been successfully used (Gruca et al. 2003; Dahan et al. 2007; Soukhoroukova 2007). Gruca et al. (2003) used Information Markets in order to forecast the success of new products. Their results show that market prices summarize the information contained in survey forecasts and improve those forecasts by reducing the variability of the forecast. In addition, Soukhoroukova (2007) used Information Markets for the assessment of new product concepts for MP3 players in order to evaluate how participants assess different characteristics before products are pushed into the market. Furthermore, Soukhoroukova (2007) compared the results of 8-12 traders to a conjoint analysis of 307 participants and found out that results of the Information Market were more robust for different price measures. Altogether, the usage of Information Markets increases the likelihood of finding the right decision and obtaining a more comprehensive information pool by involving a large sample of participants (Ozer 2005; Surowiecki 2004).

In the next section, Innovation Management in a project context focussing inter-organizational service innovation assessment will be described briefly. The project combines aspects of the innovation management approaches mentioned in Section 2.1 and develops tools and methods to support innovation management in inter-organizational contexts.

3.4.3.1 Research Project Use Case: TEXO

While the service sector is one of the biggest employers in Germany, a large-scale German research project was launched in 2007 in order to develop a holistic approach for the management of dynamic Business Networks (BN). The project named TEXO[20] consists of a platform, models, methods and components to realize a supportive system to bring together service providers and service consumers. Therefore, an open standard infrastructure to offer and deliver services is an essential prerequisite. Allowing the composition to build services based on several sub services is of central relevance to offer value added services. Offering and trading these services via a web-based service platform allows the easy access of service providers as well as service consumers. Moreover, service providers may adapt their

[20]The TEXO project is funded by the Federal Ministry of Education and Research (support code 01MQ07012), duration of 4 years (03/2007-02/2011).

services to offer them to a specific group of consumers with different business models. A comprehensive description of the TEXO concept can be found in Janiesch et al. (2008).

3.4.3.2 TEXO Innovation Life-Cycle and Methods

As mentioned in Section 2.1.4, innovation assessment plays also an important role in inter-organizational contexts. Academia offers several approaches for the management of innovations. The described approaches in Section 2.1.2 provide descriptions how innovation management can be implemented, but lack concrete tools and methods for the fulfillment of single steps. The innovation management in TEXO was designed to utilize the advantages of a continuous innovation model similar to the innovation wheel of Hamel (2002) and developed tools and concepts for the conduction of tasks in innovation management. One of the first activities during the creation of new services is the innovation phase. This phase supports the development of new services through the provision of methods and tools for the innovation life-cycle. The TEXO innovation process is depicted in Figure 3.6.

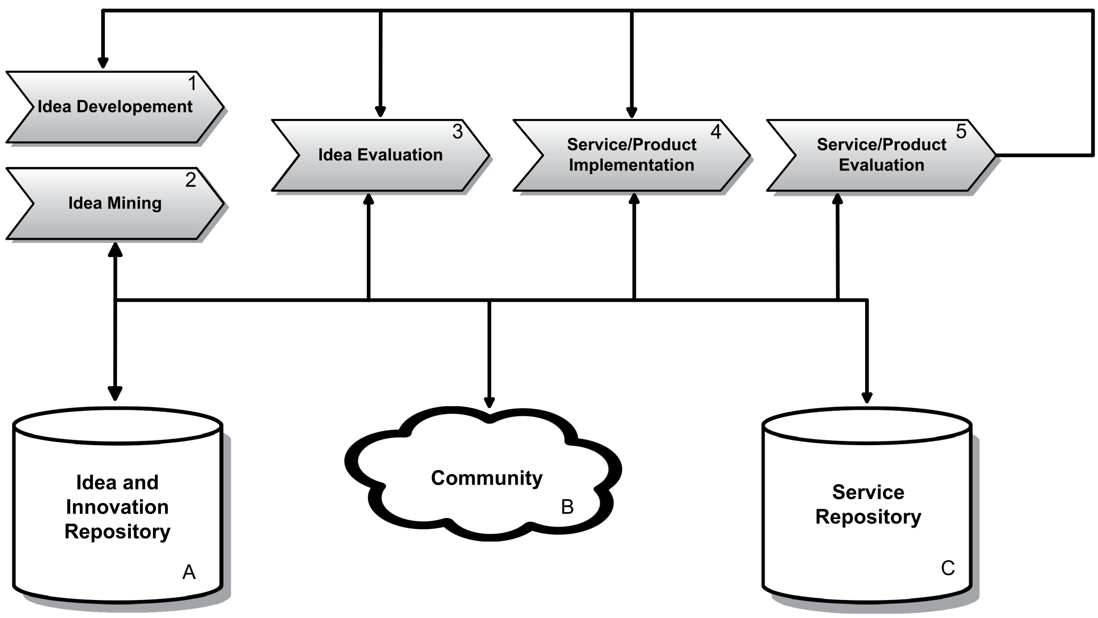


Figure 3.6: TEXO Service Innovation Model

In early product and service stages respectively, an innovation idea usually is developed either by inspiration or clever combination of fragments.[21] Therefore, the innovation life-cycle starts with two phases (Phase 1 and 2) of how ideas may enter the life-cycle. Typically, such an idea generation is done in group workshops or think tanks where the result is stored in the idea/innovation repository (A). After the idea generation, the developed ideas and innovation alternatives can be evaluated through communities (B) in phase 3. Once idea alternatives have been

[21] Methods to support the creation of ideas and further information can be found in: Diehl and Stroebe (1987), Potter and Balthazard (2004), Simonton (1999), Toubia (2006), Goldenberg et al. (1999), Troy et al. (2001), Hender et al. (2002), Pinsonneault et al. (1999), Piller and Walcher (2006).

evaluated by the community, the idea can be (prototypically) implemented (Phase 4). To evaluate if the community accepts services or products, an evaluation phase collects opinions as well as usage information from the community (Phase 5) based on information derived from the service repository (C). The result obtained at the end of the five phases may be reused as feedback for the prior phases in order to initiate new ideas or refine already implemented services.

The advantage of the innovation life-cycle is that loosely organized participants in Business Value Networks can be integrated in every stage of the process. For example, the assessment of innovations via an Information Market allows market operators to invite people to register to the web-based market system easily. Furthermore, a relevant fraction of the TEXO community may take part in brainstorming sessions whereas another fraction is evaluating the most promising ideas via an Information Market. While participants in the community are customers as well, they can actively influence and steer innovation of their own interest. Furthermore, they can track the impact of their trading activity as well as the aggregation of all traders' estimations in the market directly after trading in real time. The TEXO innovation life-cycle overcomes therefore the drawbacks of state-of-the-art models. For instance, feedback loops in every phase allow the continuous improvement in any phase. If results of the feedback analysis indicate that early innovations needs to be improved, a new innovation cycle can be triggered beginning in Phase 1. Thus, the community can again assess improved innovation proposals via an Information Market in a second step. By monitoring service usage continuously (Phase 5), feedback about the usage is collected in order to derive, if a service needs to be reinvented or if new services seem necessary based on community feedbacks. Altogether, Information Markets are used as a method to assess information from prior phases in an ad hoc and flexible manner as an integral part of the TEXO innovation life-cycle.

3.4.4 Other Fields of Application

In scientific literature, the usage of Information Markets is also reported for various objectives. Nearly all kinds of future events can be represented as contracts and evaluated in fields of public interest ranging from technical to socio-political issues (Pennock et al. 2001b). Therefore, scientists experimented in different domains. Due to the logic of the payout mechanism, Information Markets are apparently suitable for short-term and medium-term forecasting of events in order to observe their outcomes. These outcomes form the base for the payout and, thus, determine the success of participating traders. Transferring this to long term forecasting, one would have to wait for the outcome of the event in order to determine the payments. Yet, traders are not willing to invest time in an Information Market and wait several years for their payment. In order to tackle this issue, Hanson introduced *Idea Futures* for long term forecasting and argues that "[...] future markets in ideas could help the evolution of ideas by creating a visible consensus of relevant experts, and better incentives for honesty and care when making contributions." (Hanson 1992). Thus, traders obviously do accept Information Markets for long term forecasting.

In Yahoo's Tech Buzz Game[22] users predict technologies that Internet users will be searching for in the future (Mangold et al. 2005). Users are paid out according to the number of search requests as a benchmark. Once the topic becomes uninteresting, the markets will be closed. In parallel, Yahoo's Tech Buzz Game tries to predict the popularity of smart phone operating systems, e.g., Apple's iOS or Google's Android. In parallel, the search frequency of these technologies is ranked based on their search frequency in internet search engines. Depending on this ranking, traders can be paid out. Once the search frequency drops, it can be assumed that the overall interest in these technologies is decreasing and the markets close.

In the field of economic indicators, Information Markets are used to aggregate expectations of people about the development of important economic variables like inflation rates, gross domestic product or unemployment rates (Berlemann 2001; Gürkaynak and Wolfers 2005). From November 2009 till October 2010, a large field experiment with nearly 1.000 registered users[23] is operating named EIX – Economic Indicators Exchange[24]. Beginning in November 2010, it is extended to another year of run-time till October 2011. In the EIX, play money is given to registered traders. Based on their individual forecasting performance, they can win monthly prices worth ranging from 175 € to 500 €. In November 2010, four major prizes are raffled for the traders with the best overall performance in the first year. Contracts about export, inflation, unemployment, the gross domestic product and industry investments for Germany can be traded three periods in advance and in parallel along the publication of terminal values through the Federal Statistical Office[25]. Once the terminal values are available, shares are paid out according to these values.

Other markets try to forecast political risks (Hulse 2003). Even in the medical domain, Information Markets are used to forecast infectious disease activity (Polgreen et al. 2007). A very popular application of Information Markets is the Hollywood Stock Exchange[26] (HSX). The HSX was introduced in 1996 and is an example of a very successful application of Information Markets for years. The HSX forecasts box office numbers for cinema movies as well as contracts representing the popularity of actors and movies. The HSX shows very accurate forecasts regularly (Pennock et al. 2001a; Wolfers and Zitzewitz 2004; Lamare 2007). Information Markets are also used to predict market capitalization of companies like Google. The prediction markets forecasted Google's post-IPO market capitalization accurately (Berg et al. 2009).

3.5 Challenges & Summary

In the previous sections the fundamentals of markets were described in order to show how complex the design of markets is concerning the decisions a market engineer has to consider. In Information Markets, the market design has a strong effect on the overall success of the market. Many Information Markets rely on

[22] http://buzz.research.yahoo.com
[23] 1.000 registered users as of September 2010.
[24] http://eix-market.de
[25] http://www.destatis.de
[26] http://www.hsx.com

virtual money. One of the main challenges is to retain the participants activity in the market. In financial markets, in which traders are incentivized via their own real money investments, it is difficult for traders to quit trading once their portfolio dropped below the initial value. In play money Information Markets, traders can quit trading at every time. If their portfolio value drops below the initial value and they feel that it is too tedious to stick to the market, it is likely that they drop out – with no disadvantage. Therefore, incentives have to be designed that even traders who are likely to quit the market have an incentive to actually stay in. On the one hand, one can argue that "unsuccessful" traders are not necessarily needed in markets because they do not contribute information to bring prices in the right direction. But they provide further liquidity to informed traders and are a valuable in Information Markets. On the other hand, every trader brings a piece of information visible to other traders. Other traders update their beliefs and therefore the overall performance of the Information Market may improve.

In this context, it is of utmost importance that several aspects of an Information Market are factored in and carefully designed in order to implement a successful market. As mentioned before, the selection of traders is an important issue. The right target group needs to be identified containing people carrying relevant information and having beliefs about the forecasting objective of the Information Market. This is highly relevant for enterprises, where it has to be decided which group should be invited to the market. It can be decided to use an open, a closed or even a mixed group of employees, customers, suppliers or consultants.

Furthermore, the contract design needs to be simple and intuitive. Contracts which are hard to understand may restrain Information Market novices from using the market regularly. In order to provide traders in Information Markets useful information about the contracts, several methods of information provisioning are to be considered. Newsletters or news feeds are helpful as information source for traders. Thus, as mentioned in Section 3.1, the engineering of successful market design is a challenging task. Especially in field experiments, as explained in Section 3.4, it is crucial to design an Information Market carefully. An inappropriate market design conceals the latent risk of getting lost or being not encouraged to reveal their true beliefs and expectations. For example, during the 2002 FIFA Soccer World Championship, Schmidt et al. (2008) operated an Information Market to predict the outcome of 64 matches and compared the forecasts to Bookmakers quotes and a random predictor. The results of the Information Market were contradictory to what one would expect. The Information Market produced weak results which were extremely inaccurate. In other Information Markets predicting soccer results, the accuracy was at least as good as the benchmarks.[27] Schmidt et al. (2008) state that after their analysis the results seemed to be distorted due to a structural problem of the markets' design. They suspect that biases of traders lead them to poor predictions and caused therefore a low overall prediction accuracy. If the market design would have been designed to avoid biases, the results would maybe have shown better predictive accuracy. Therefore, especially in field experiments, the market design is of utmost importance to avoid market failures.

[27]European Championship 2000 (Schmidt and Werwatz 2002), FIFA World Soccer Championship 2006 (Luckner 2008)

On the other hand, some markets' designs obviously do not offer reasons for failures. Sometimes traders themselves bear a potential for inaccurate market results of which a market engineer should be aware of. Several reports describe the favorite long shot bias as a reason for market inefficiencies (Ali 1977; Hausch et al. 1981; Thaler and Ziemba 1988). Traders tend to overestimate their own favorites and undervalue common favorites. Therefore, bettors' misperceptions of probability drive the favorite long shot bias (Snowberg and Wolfers 2007). The favorite long shot bias may thus be considered as the result of inefficient markets (Woodland and Woodland 1994). In Information Markets field experiments, long shot bias effects are often observable and are to be considered (Berg and Rietz 2002; Wolfers and Zitzewitz 2004; Leigh et al. 2007; Luckner 2008). In order to avoid biases, the market engineer has to identify situations in which biases may occur and design an appropriate part of the incentive scheme in order to bring traders not to follow their biases. If the market design is appropriate, Information Markets may outperform natural benchmarks[28] like polls or experts regularly, even if traders in Information Markets are biased (Brüggelambert 1999; Forsythe et al. 1999; Berg et al. 2000; Berlemann and Schmidt 2001; Spann 2002; Berg et al. 2008; Graefe 2008b; Stix 2008).

As mentioned in Section 2.1, the outcome of Information Markets for innovation assessment cannot be exactly determined in order to payout traders. Therefore, the design of an appropriate substitute is one of the substantial challenges of market engineering. Moreover, employees in EIM may trade following their estimation, based on which innovation they prefer instead of which innovation is the most beneficial one for the company. In order to bring employees to trade in line with the objective of the Information Market, the challenge lies in the appropriate and intuitive design of contracts and the incentive system.

Another serious issue in Information Markets is manipulation. In former political stock markets a group of traders tried to distort prices of their favorite candidate. But the market quickly detected the inappropriate prices and within 24 hours, prices rebounded to the previous level again (Hanson et al. 2006). Hanson and Oprea (2004) investigated that Information Markets cannot be manipulated in terms of price manipulations because traders are keen on identifying inappropriate prices in order to exploit them. The prerequisite in liquid markets is, therefore, that there are enough traders constantly observing price movements and that enough liquidity is available. Another type of manipulation is the usage of automated trading mechanisms (bots) or multiple accounts. Since most Information Markets operate with play money and do not charge fees for participation, traders may register multiple times in order to move virtual money from one account to another. In the STOCCER field experiment during the FIFA[29] World Cup in 2006, several traders registered multiple accounts and tried to exploit them. This challenge can be faced with a fraud detection tool. Blume et al. (2008) developed a monitoring tool capable of identifying suspicious price movements and trading activities to some extend. It can mark the relevant accounts autonomously following certain strategies

[28]Possible benchmarks are explained in Section 2.2.
[29]Fédération Internationale de Football Association

and tags accounts for manual inspection. It is a helpful tool in order to face the threat of possible manipulative activities in Information Markets.

Summarizing, this section provided insights of important aspects a market engineer has to consider while setting up an Information Market. Several of the described challenges are picked up again in the following Part II, where two field experiments are introduced. Both of them were individually designed to be operated in different contexts whereas the design of the mentioned challenges played a vital role and took most of the time during the market system development.

Part II

Methodology & Evaluation

4 The Impact of Market Making on Information Markets

In this chapter, the impact of automated market making on the forecasting accuracy, market liquidity as well as information efficiency of Information Markets is described. As mentioned in Section 3.3.4, market making is an important concept to keep markets liquid as well as to improve market quality. Market makers are usually used to support trading activity by providing bid and ask orders in stock markets. Mostly, market makers are human entities in real money markets like the New York Stock Exchange[1] (NYSE) or the Frankfurter Börse[2]. In general, market makers pursue several objectives besides making money through their trading activity (Schwartz et al. 2006).

The classic role of market making is the provision of immediacy through the provision of continuous trading. The market maker is continuously present, buying when a public seller arrives and selling when a public buyer arrives. It is the medium through which public buyers and sellers effectively meet each other. Another objective is the provisioning of liquidity. A market maker will commonly trade for larger order sizes that it is quoting. The ultimate source of liquidity are still public buyers and sellers. The market maker simply helps them to come together and cannot be the ultimate source of liquidity. Furthermore, market makers animate markets while bringing liquidity to less liquid stocks as a facilitator. Moreover, they support price discovery processes while offering buy and sell shares continuously. Summarizing, market makers have several important roles to play. These are the provisioning of capital, animating the market, participating in price discovery and fostering price improvements. Generally, illiquidity is a serious problem in markets (Schwartz et al. 2006). Markets are like networks in which traders are nodes depending on each other. Once a trader demands liquidity there has to be a liquidity providing counterpart. The more traders join the network, the more frequent the overall trading activity will be (Schwartz et al. 2006).

[1] http://www.nyse.com
[2] http://www.boerse-frankfurt.de

When Information Markets were used in the late 1980's (cp. Section 3.2), they were mainly about forecasting of political and sports events. The liquidity in such topics does not very often lead to a problem, because sports and politics are topics of common interest in the public. Almost anybody has some knowledge or expectations about who will win the football match or which candidate has a chance to win the election. Hence, almost anybody can act as a trader in Information Markets. Information and news, which may change the mind of traders, are ubiquitously available in newspapers, television or radio-broadcastings. During the 90's, the field of application expanded to other topics than politics or sports. Companies began to use Information Markets to forecast sales figures, technology impact in the future or project durations. Furthermore, public available markets like Inkling[3] came up and started offering markets to the public to forecast almost everything somebody is interested in like weather or technology breakthroughs. Moreover, Information Markets have begun to be available as web-based systems and were operated 24 hours a day, 7 days a week. Thus, human market makers are not applicable in online-based Information Markets. Therefore, this chapter investigates the impact of automated market making on market accuracy, liquidity and efficiency in a field experiment during the European Soccer Championship 2008.

As mentioned, forecasting in domains of low interest public interest may suffer from illiquidity in web-based Information Markets and, therefore, the concept of automated market making suggests itself. Many Information Markets make use of automated market makers to support trading activity. For example, popular Information Markets like Inkling[4] and the HSX[5] rely on market making. But the impact of automated market making compared to non-market maker markets has not been comprehensively analyzed in a field experiment, yet. What exactly is the impact of having a market maker in an Information Market on the forecast accuracy, the trading activity as well as the market efficiency? What effect has an automated market maker on the trading activity of traders? And, can a market maker lead to more accurate results in small-size Information Markets?

The following sections describe the field experiment conducted in 2008 which investigated the impact of market making during the European Soccer Championship. In Section 4.1, the field experiment design will be described in detail. Section 4.2 presents descriptive statistics in order to provide an indication about the overall market. Afterwards, Section 4.3 shows the hypotheses investigated during the field experiment whereas Section 4.4 introduces the results. Section 4.5 concludes the chapter.

4.1 The European Soccer Championship 2008 Experiment

The European Soccer Championship 2008 was carried out in Austria and Switzerland. The tournament started with the first matches on the 7$^{\text{th}}$ of June 2008 and ended with the final match on the 29$^{\text{th}}$ of June 2008. In total, 16 teams qualified for the tournament and were sorted into four groups as shown in Figure 4.1.

[3]http://inklingmarkets.com
[4]http://inklingmarkets.com
[5]http://www.hsx.com

Group A	Group B	Group C	Group D
Switzerland	Austria	Netherlands	Greece
Czech Republic	Croatia	Italy	Sweden
Portugal	Germany	Romania	Spain
Turkey	Poland	France	Russia

Figure 4.1: European Soccer Championship 2008 - Group Phase

The teams had to play against each of the other teams in their group and were ranked in a group ranking based on their success. In the experiment, teams were represented via contracts. Traders were supposed to trade contracts based on their expectations and beliefs following two objectives: in the first step, they were supposed to forecast the teams reaching the final round. In the second step, they were supposed to forecast the winner of the tournament.

The group phase was carried out until the 18^{th} of June 2008 and eight teams – the first and the second team of each group – qualified for the final round while the other teams dropped out of the tournament. The tournament was then organized in four quarter finals, two semi finals and the final match. That is, the eight remaining teams in the knockout stage had to qualify in each ongoing match to reach the next round. Otherwise they dropped out of the tournament. The finals took place from 19^{th} of June – 29^{th} of June 2008.

4.1.1 Experiment Design

To investigate the impact of market making, two identical markets were implemented. One was equipped with an automated market making mechanism whereby the other was not. Details about the functionalities of the automated market maker will be described in Section 4.1.2. For the experiment, it was intended to invite only a few participants to keep the two markets small in order to learn if the market without a market maker mechanism would be very illiquid and no reasonable results would occur.

Approximately 250 people were invited to participate in the market via email invitations, whereby people were allowed to forward the invitation. Altogether, only a few mailing lists were addressed in order to get small markets with approximately 40-50 participants. In total, 88 people registered as participants. Each participant was endowed with 100.000 virtual currency units (EM€) and 100 shares of each stock, in order to trade instantly. Each stock represented one corresponding team out of the 16 teams taking part in the tournament. From the 7^{th} through the 18^{th} of June participants were supposed to trade the eight teams that they expected to reach the final round of the tournament. After the group stage, the depot of every trader was paid out. Stocks in the depot of participants representing teams reaching the finals were paid out with 100 EM€, otherwise 0 EM€. After the payout, shares were taken from the market and could not be traded anymore.

From the 19th till the 29th of June, traders were again equipped with 100 shares of each team participating in the finals and were supposed to forecast the champion.

After the final match, only the shares of the winner were paid out with 100 EM€, all others with 0 EM€.

Both markets started on the 7th of June 2008. Stocks were issued at an equal price of 50 currency units. The sum of all payouts was 800 (= $8x100$) currency units and, therefore, the sum of all stock prices should be 800 on average at any time. Thus, each contract was initially issued at a price of 50 (= $\frac{800}{16}$) currency units.

Until the 18th of June 2008, the group phase was traded and was paid out after the last match of each group. On the 19th of June 2008, the market was reset and the eight teams in the final round were traded. Only the shares of the champion were paid out with 100 currency units. Therefore, the sum of all stock prices should be 100 currency units. Thus, contracts were issued at a price of 12,5 (= $\frac{100}{8}$) currency units. The final round was open until the final match on the 29th of June 2008. Figure 4.2 shows tournament overview in relation to both market phases.

Figure 4.2: Tournament Overview (Market Phases)

Traders could see the order book with all outstanding buy and sell offers continuously in the trading screen. Furthermore, they could track the evolution of transaction prices via charts representing the stock price history. Via a trading screen, they could submit limit orders by quoting the volume and price they were willing to buy/sell. In the depot screen, they could see their already executed orders and actual depot details. All traders were ranked according to their depot value in a ranking, which was accessible to all traders.[6] The depot value included the trader's available money as well as contracts in the depot. The prices of contracts in the depot were valuated according to the current stock price. Changing stock prices could therefore affect the depot value. A selection of screen shots illustrates the market system in Appendix A, Figures A.7 - A.12.

As incentives, prizes were raffled among participants. All depot values were summarized and the fraction for each trader' depot value was calculated in percent (%). This indicated the winning probability of each trader according to the depot value. The winning probability was displayed in the ranking as well. After the tournament, an iPod worth 125 € was raffled in each market. A trader with a higher winning probability had higher chances to win the prize. Traders could realize profits once they started trading. Hence, early traders had an advantage compared to traders entering the market several days later. With the winning probability, even late traders had a chance to improve their winning chances. This was intended to motivate traders who had entered the market late. In contrast to traditional strategies where traders with the highest depot value are allowed to win prizes, it is advantageous to motivate late traders before they quit trading if they feel that they cannot catch up to other traders. For the draw of winners, random numbers were assigned to traders according to their winning probability and a random number was drawn in order to allot the winner.

The experiment used an continuous double auction mechanism (CDA) in order to allow the immediate execution of orders. Once a trader submitted an order, it was executed with a counter order. Therefore, traders could provide their information at any time. In contrast, a call auction does not provide a continuous order matching mechanism. As mentioned in Section 3.1.3, orders are stored whereas the matching is done at a pre-defined point in time. Since information in the context experiment appears continuously, the CDA mechanism was used to allow traders the immediate provision of their information.

4.1.2 Market Maker Mechanism

As mentioned in Section 4.1.1, one of the two markets employed a market maker mechanism in order to avoid situations of illiquidity. The functionality of the implemented market maker mechanism focused on two aspects: The provision of liquidity and arbitrage trading at any time.

The liquidity providing functionality intends to offer immediate trading capabilities for traders. The market maker is implemented as an automated piece of software equipped with a trading strategy. As mentioned in Section 3.3.4.1, a CDA mechanism reveals open orders in an order book. Other mechanisms do not offer that kind of information revelation. For the experiment, thus, a market maker mechanism was implemented in a CDA mechanism which functions will be described in the following.

Once a trader initiates a trade via a corresponding bid or ask offer, a new transaction price occurs. This new transaction price triggers the automated market maker

[6]It was ensured, that traders from the MM market could not see the NMM market and vice versa.

to react. Once it observes a new transaction price, it put an ask offer in the market at +1 % above the new transaction price and a bid offer at -1 % below the new transaction price analoguously. In each offer, it put 50 shares. Once another transaction happens, it deletes its old offers and the remaining shares in case of a partly executed offer and sets two new offers at +/-1 % around the new transaction price. Hence, traders may trade at any time with a counterpart in the market and the market maker reacts only if a human trader causes a new transaction. This strategy was developed in order to investigate, if a simple strategy works well and has a positive effect on trading activity, market efficiency and accuracy. If this strategy fulfills these objectives, it can be assumed that even more sophisticated strategies will also show positive effects. Figure 4.3 illustrates the market maker strategy.

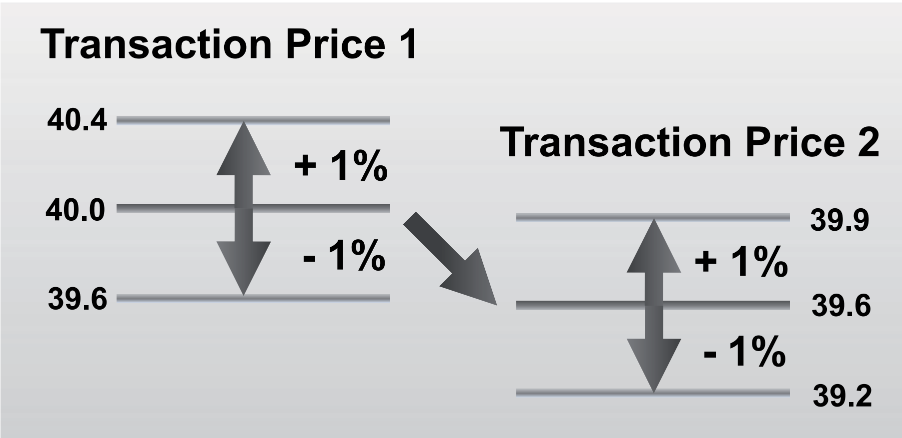


Figure 4.3: Market Maker Strategy

On the left hand side, the current situation of the transaction price is given by 40 currency units. The market maker puts a sell order at 40.4 and a corresponding buy order at 36.6 currency units. After a transaction happened at 36.6, the new transaction price is 36.6. The market maker deletes his old orders and submits two new orders at 36.96 (sell) and 36.23 (buy).

Moreover, the market supported portfolio trading in order to buy or sell shares to the operator for a given price. Portfolio trading is intended to keep market prices efficient. Traders could buy or sell 1 share of each stock for 800 currency units during the group market from the market operator. Analogously, the portfolio in the final round cost 100 currency units – the sum of the payouts in the final round. Traders can use the portfolio trading in two ways:

1. The sum of all stock prices is higher than the sum of the total payout
2. The sum of all stock prices is lower than the sum of the total payout

In the first case it is reasonable to buy portfolios and sell them to the market. While the sum of all stock prices is higher than the price of a portfolio, the trader makes riskless profits by selling shares to the market. In the second case, traders should buy stocks in the market and sell them with profit to the market operator. This is also called *arbitrage trading*. Traders were allowed to do arbitrage trading at any time during the market runtime.

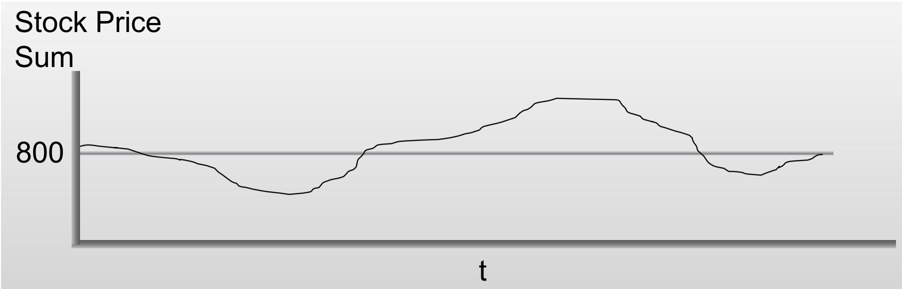


Figure 4.4: Arbitrage Trading

Figure 4.4 shows the function of the market maker arbitrage trading strategy. The market maker checked after each trading activity, if in case of the group phase the sum of all stocks was 800 currency units, during the final round 100 currency units respectively. The areas above the horizontal line indicate an overvaluation[7] of the market whereas areas below the horizontal line indicate an undervaluation[8]. If the sum differed more than +/-5 % currency units, the market maker began to trade in every stock following a trading strategy which will be described in the following.

Assuming that the sum of all stocks is 850 instead of 800, the market maker tries to bring the sum down by 50 currency units between 760 and 840. First, it assigns the 50 currency units to each stock regarding the current stock price of each stock. Hence, stocks with high prices will be more affected than stocks with lower prices. This is to ensure that the relation between stocks is retained. If the market maker tries to trade all stocks down linearly, the relation of high priced stocks and low priced stocks is changed. Imagine, if a stock is traded at 1 currency unit and the market maker tries to bring all 16 stocks down by $\frac{50}{16} = 3.125$, the linear strategy would lead to a negative stock price in that case. Therefore, the market maker used the following strategy to avoid the described distortion of stock price relation.

Remembering the 50 currency units to bring the sum of all stocks down, the strategy normalizes all stock prices to 1 and calculates the weight of each stock based on the stocks' fraction related to all stocks. For example, if three stocks are in the market priced 100;30;20 and the total payout is 100, the weights of stocks calculates to $\frac{100}{150} = 0.666$; $\frac{30}{150} = 0.200$; $\frac{20}{150} = 0.133$. Thus, the strategy of the market maker is to trade the first stock down by $50 * 0.666 = 33.33$ currency units, the second stock by $50 * 0.2 = 10$ currency units and the third stock by $50 * 0.133 = 6.65$. The higher a stock price is, the more it will be affected by the market maker. The strategy follows a distribution of $\frac{1}{x}$. Figure 4.5 shows the functioning of the described strategy. The black panels represent the original overvalued stocks whereas the dark-gray panels represent the resulting stock prices reduced by the automated market maker (light-gray panels).

With these two functionalities of raising stock values up and down and to keep them on a certain level, two major objectives of liquidity provisioning and arbitrage trading essential for thinly traded Information Markets are achieved. First, traders were able to find a trading partner permanently. The liquidity spending market

[7]The sum of all stock prices is higher than the sum of the total payout.

[8]The sum of all stock prices is lower than the sum of the total payout.

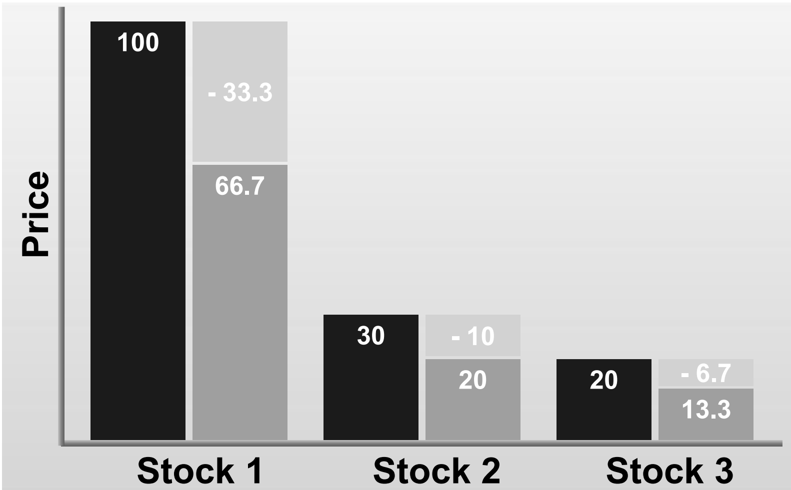


Figure 4.5: Arbitrage Example

maker is triggered by transactions of human traders. Hence, it reacts on information brought by traders. Secondly, the arbitrage functionality of the market maker ensured that stock prices always summed up to the total sum of the payouts. This functionality ensured that unexperienced traders could not set prices to an absurd level. To avoid them from dropping the market due to implausible perception, the arbitrage functionality helps to keep stock prices in a sensible range without losing the information content of stock prices.

4.1.3 Technical Design

The market in the field experiment was developed to create a market system which is easy to maintain and which can be extended by services and functionalities with manageable effort. The system was developed with Groovy&Grails[9]. The market system is then compiled to be deployed into an application server, e.g., Apache Tomcat[10], to get it online. An underlying database system keeps all relevant data required for the market system. Figure 4.6 shows the basic system architecture.

Traders could connect to the market via http://www.em-stoxx.de at any time. On the start page, they had to login with their personalized user name and password. The necessary data for authentication and trading activities were accessed in the MySQL database[11] via the Application logic. This was necessary to recognize and authenticate each trader at any time to assign depots and money to the trader. New users could get a user name and a password through a registration process free of charge. During registration, a unique email address and a user name was necessary to join the market. Traders had to agree to the Standard Business Terms[12]. In order to avoid automated bidding, the usage of bots and automated trading mechanisms was strictly forbidden by the SBT. Each clue of automated functionality during market runtime was investigated and would have led to the disqualification of traders

[9] http://www.grails.org
[10] http://tomcat.apache.org
[11] http://www.mysql.com
[12] *engl: Standard Business Terms (SBT)*, Allgemeine Geschäftsbedingungen (AGB), cp. Appendix A, Figure A.9

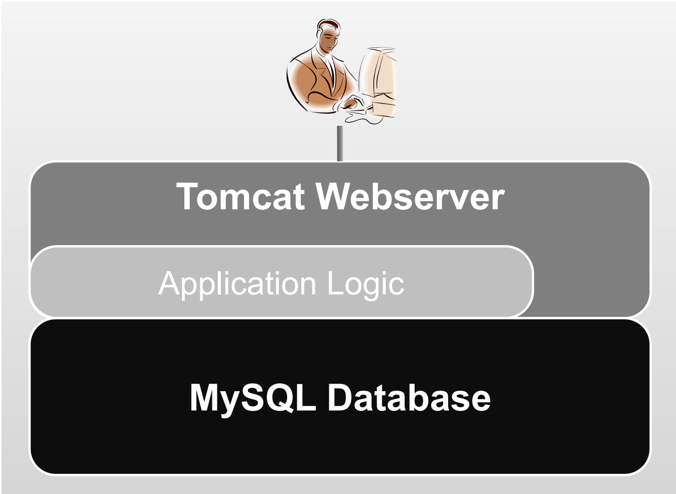


Figure 4.6: System Architecture

violating the SBT. During market runtime, the trading activity was monitored with an automated analysis tool, which monitored each trade. Indicators for automated trading were, e.g., very short time between several trades or the observation of several trades in one stock with unrealistic prices between two traders or a group of traders.[13] The used automated market monitoring tool introduced by Blume et al. (2008) allowed real time and ex post market monitoring. One could adjust several parameters on which issue the tool should focus. During market runtime, no conspicious trading activity was monitored. It may have happened that some smart traders anyhow tricked the market which was not detectable by the monitoring tool nor by manual inspection. On the other hand, Hanson and Oprea (2004) showed that a proportion of "manipulative" trading activity may be advantageous in Information Markets.

4.2 Descriptive Statistics

For an initial overview, Table 4.1 illustrates the complete tournament results. The columns MM and NMM show the last trading price in both markets before the match started for each team. The winner as well as the second best team at the end of the group phase qualified for the quarter finals.

Each price was taken before the match began. It was assumed, that these prices reflected the collective estimation of all traders, and that the team with the higher stock price would win the match. For example, the final match prices on the 29th of June 2008 were 55.7 for Germany and 40.0 for Spain in the market maker market. Thus, traders supposed Germany would win in this case. In Section 4.4.2, several measures and benchmarks will be introduced to describe the accuracy of both markets in detail.

Table 4.2 shows basic statistics of both markets. Registrations were equally distributed with 44 participants, although the number of active participants was 33 in

[13] This indicates that one trader or a group of traders established several accounts and transferred money from one account to another via fake trades.

Table 4.1: Tournament Overview

Date	Match (Team 1 - Team 2)	Last Price MM Team 1	MM Team 2	NMM Team 1	NMM Team 2	Result
		Group A				
07 June 2008	Switzerland - Czech Republic	40.40	53.00	70.00	55.00	0:1 (✔,✖)
07 June 2008	Portugal - Turkey	70.00	40.40	60.00	55.00	2:0 (✔,✔)
11 June 2008	Czech Republic - Portugal	55.30	91.30	50.00	60.00	1:3 (✔,✔)
11 June 2008	Switzerland - Turkey	21.00	1.40	12.00	20.00	1:2 (✖,✔)
15 June 2008	Switzerland - Portugal	0.80	85.00	5.00	101.00	2:0 (✖,✖)
15 June 2008	Turkey - Czech Republic	25.90	58.70	80.00	95.00	3:2 (✖,✖)
		Group B				
08 June 2008	Austria - Croatia	22.40	60.00	20.00	75.00	0:1 (✔,✔)
08 June 2008	Germany - Poland	80.00	35.80	95.00	40.00	2:0 (✔,✔)
12 June 2008	Croatia - Germany	40.10	82.00	80.00	125.00	2:1 (✖,✖)
12 June 2008	Austria - Poland	50.60	27.20	11.00	5.00	1:1 (✖,✖)
16 June 2008	Austria - Germany	50.00	90.00	5.00	100.00	0:1 (✔,✔)
16 June 2008	Poland - Croatia	8.00	99.60	5.00	99.00	0:1 (✔,✔)
		Group C				
09 June 2008	Romania - France	21.60	90.00	70.00	90.00	0:0 (✖,✖)
09 June 2008	Netherlands - Italy	29.40	100.00	35.00	100.00	3:0 (✖,✖)
13 June 2008	Italy - Romania	80.00	20.00	75.00	35.00	1:1 (✖,✖)
13 June 2008	Netherlands - France	75.40	67.20	101.00	95.00	4:1 (✔,✔)
17 June 2008	France - Italy	25.80	29.50	100.00	70.00	0:2 (✔,✖)
17 June 2008	Netherlands - Romania	100.00	43.20	119.00	35.00	2:0 (✔,✔)
		Group D				
10 June 2008	Spain - Russia	80.00	33.00	92.00	52.00	4:1 (✔,✔)
10 June 2008	Greece - Sweden	23.90	50.00	20.00	90.00	0:2 (✔,✔)
14 June 2008	Sweden - Spain	36.90	82.90	95.00	102.00	1:2 (✔,✔)
14 June 2008	Greece - Russia	20.00	28.40	95.00	5.00	0:1 (✔,✖)
18 June 2008	Greece - Spain	0.05	100.00	95.00	90.00	1:2 (✔,✖)
18 June 2008	Russia - Sweden	64.70	26.90	90.00	95.00	2:0 (✔,✖)
		Quarter Finals				
19 June 2008	Portugal - Germany	35.00	2.70	60.00	35.00	2:3 (✖,✖)
20 June 2008	Croatia - Turkey	6.20	2.00	55.00	40.00	1:3 PSO (✖,✖)
21 June 2008	Netherlands - Russia	42.20	3.50	95.00	34.00	1:3 E.T. (✖,✖)
22 June 2008	Spain - Italy	13.00	7.00	70.00	40.00	4:2 PSO (✔,✔)
		Semi Finals				
25 June 2008	Germany - Turkey	70.00	5.60	95.00	34.00	3:2 (✔,✔)
26 June 2008	Russia - Spain	7.10	10.00	35.00	70.00	0:3 (✔,✔)
		Final Match				
29 June 2008	Germany - Spain	55.70	40.00	95.00	90.00	0:1 (✖,✖)

the market maker market and 35 in the non-market maker market. A participant is denoted as "active" if he conducted at least one transaction. In total, 11.265 transactions were monitored in the market maker market compared to 346 in the non-market maker market. The total number of transactions includes every transaction incl. those from the market maker. The number of transactions caused by either human traders or the market maker are differentiated in the next three rows. In the following, the nomenclature M-M, M-H, H-M and H-H is explained.

- M-M: Transaction occurred between the market maker. The market maker traded with itself.
- M-H: Transaction occurred from the market maker on the buy side and a human trader on the sell side
- H-M: Transaction occurred from a human trader on the buy side and the market maker on the sell side
- H-H: Transaction occurred between two human traders

Table 4.2: Market Liquidity

	MM Market	**NMM Market**
# Participants	44	44
# active Participants	33	35
Transactions total	11.265	346
Transactions M-M	6981	./.
Transactions M-H/H-M	3.877 (1.473/2.404)	./.
Transactions H-H	407	346
Transactions per trader (⌀)	152**	24
Transactions per trader per day (⌀)	6,5*	1
# Orders/day (⌀)	1.423	15
# shares/day (⌀)	33.246	1.631
# of marketable limit orders (⌀, human active)	17,12*	2,15
# of marketable limit orders (⌀, human passive)	4,81*	1,92
# trades in 24h (⌀)	179*	18
# of shares per trade in 24h (⌀)	195	99
Trade size in € Vol. (⌀)	2307	6281**
Trade size (# Shares per Trade, ⌀)	97	108
Quoted Spread (bps, ⌀)	1616**	2515
Quoted Spread (bps, σ)	2580	2274
Quoted Spread Trade (bps, ⌀)	602*	2120
Quoted Spread Trade (bps, σ)	1279	2226
Effective Spread (bps, ⌀)	651**	2582
Effective Spread (bps, σ)	1401	6976

Significance: (*) 1 % level, (**) 5 % level, t-test

A further analysis about the composition of transactions was conducted and will be described in Section 4.4.1. An indication for the liquidity of markets is the analysis of spreads. Liquidity represents the transaction cost market participants face to trade. A measure for the liquidity is an asset's ability to be sold rapidly, with minimal loss of value at any time (Harris 2003). Quoted spreads are a simple, commonly used measure of trading costs and can easily be calculated using trade and order data. All calculations presented in Table 4.2 are spreads relative to stock prices and are reported in basis points (bps). Let $Ask_{i,t}$ be the ask price for a stock i at time t and $Bid_{i,t}$ the respective bid price. $Mid_{i,t}$ denotes the mid quote then the quoted spread is calculated as follows:

$$\text{Quoted Spread}_{i,t} = \frac{(\text{Ask}_{i,t} - \text{Bid}_{i,t})}{2 * \text{Mid}_{i,t}} \tag{4.1}$$

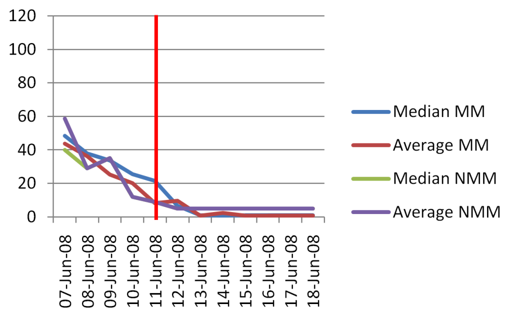
Additionally, one can separate quoted spread and quoted spread at trade. Quoted spreads include all order book changes whereas quoted spreads at trade are limited to quotes just before a trade is executed. The effective spread is the spread when an incoming market order is directly executed with a counter order. Let $Price_{i,t}$ be the execution price then the effective spread is defined as

$$\text{Effective Spread}_{i,t} = \frac{(\text{Price}_{i,t} - \text{Mid}_{i,t})}{\text{Mid}_{i,t}} \tag{4.2}$$

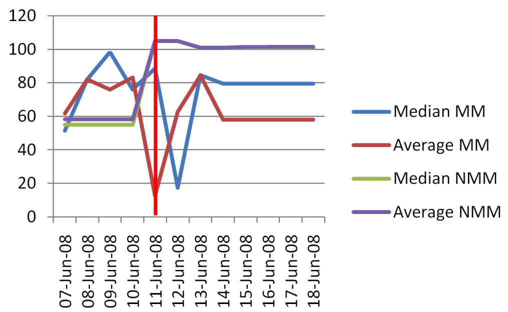
The effective spread indicates how deep an order matches in the order book. The measure must therefore be higher or equal than the quoted spread at trade at any time. The lower the spread measures are, the less transaction costs traders have to face.

Traders in the MM market did 152 transactions on average whereas traders in the NMM market did only 24. The number of marketable limit orders, which means that an order caused a transaction directly with a matching counter order was more than eight times higher in the MM market. The average number of marketable limit orders where a human trader was passive is 4.81 and, thus, lower than the number where human traders were active. This indicated that traders actively hit more existing orders directly than being executed by counter trades. Concerning the spread sizes, the MM market showed narrower spread sizes on average in quoted spread, quoted spreads at trade time as well as the effective spread. The fact that quoted spreads at trade are on average lower than quoted spreads indicate that traders mainly traded when spreads were narrow and, thus, transaction costs are low. The effective spread is slightly higher than the quoted spread at trade because it considers the level of how deep an order matches orders in the order book. If an order hits only the first level (ask or bid) in the order book, the quoted spread at trade and the effective spread are equal.

In order to visualize the changes in stock prices over time, Figure 4.7 shows the stock price history exemplary for two teams. All charts for all teams are shown in Appendix A, Figures A.1 - A.6. Figure 4.7 shows the evolution of stock prices for Switzerland and Portugal.



(a) Switzerland



(b) Portugal

Figure 4.7: Evolution of Transaction Prices

In Figure 4.7(a), the evolution of daily transaction prices is shown for the contract representing Switzerland exemplary. The lines represent the median as well as average data for both markets. The course of the transaction prices starts between 40 and 60 currency units. The negative trend indicates that traders assessed the likelihood of Switzerland reaching the finals lower than in the beginning. The red vertical line indicates the day once it was clear that a team reached the finals or not. On the 11th of June, Switzerland lost the second match and dropped out of the tournament before their third match. Regarding the results from the other teams in Group A, they did not have a theoretical chance to reach the finals. Interestingly, trade prices reacted hesitantly and reflected the collapse of Switzerland two days later with a trading price close to 0. On the 15th of June, the last group matches were carried out and after that, contracts of that group were paid out. Accordingly, contracts of group B were paid out at the 16th of June and so on.

In case of Portugal, which is shown in Figure 4.7(b), traders in both markets moved transaction prices till the 14th of June although Portugal definitely reached the final round after their second match on the 11th of June. Therefore, the prediction in case of Portugal ended at that day and trading prices were disregarded for further investigations in this work. Trading after a team definitely reached the final round distorts market accuracy and does not add further information. The payout of group A was on the 15th of June because on that day the final matches of that group took place. Therefore the whole group was paid out after the last match once the final results were available. For the design of further markets, it should be investigated if some contracts should be paid out early once their forecast is needless due to premature events to avoid price distortions, manipulation and effects on market accuracy.

Market accuracy seems to have a relation to the sizes of spreads in the introduced market. In order to further investigate spread measures in more detail, an analysis of spreads for each team was conducted and is shown in Table 4.3[14] for both markets on average per team during the group phase. The average quoted spread, the quoted spread at trade as well as the effective spread in the MM are significantly lower than the average quoted spread in the NMM. With lower spreads, it seems that the accuracy as well as the trading activity increase because traders are more likely to trade if spreads are narrow and therefore transaction costs are lower. Effects of market making on trading activity will be further analyzed in Section 4.4.1. The effect on accuracy and error measures will then be described in Sections 4.4.2 and 4.4.3.

Table 4.3: Spread Analysis

		Quoted Spread		Quoted Spread Trade		Effective Spread	
Team	Sample	MM	NMM	MM	NMM	MM	NMM
Austria	Complete	501	5397	373	4396	385	17968
	Group	501	5397	373	4396	385	17968
	Finals	-	-	-	-	-	-
Switzerland	Complete	2274	7413	496	6956	579	6956
	Group	2274	7413	496	6956	579	6956
	Finals	-	-	-	-	-	-
Germany	Complete	1451	2767	697	2242	833	2242
	Group	711	1214	504	795	571	795
	Finals	1593	7273	728	6903	876	6903
Greece	Complete	1845	351	574	263	575	263
	Group	1845	351	574	263	575	263
	Finals	-	-	-	-	-	-
Czech Republic	Complete	535	1468	407	809	415	809
	Group	535	1468	407	809	415	809

Continued on next page

[14]The analysis of quoted spreads, quoted spreads at trade time and effective spreads was conducted for each contract/team in basis points. A basis point is $\frac{1}{10000}$ of a currency unit. The analysis differentiates the complete sample per contract, the group phase as well as the finals.

Table 4.3 – continued from previous page

Team	Sample	Quoted Spread MM	Quoted Spread NMM	Quoted Spread Trade MM	Quoted Spread Trade NMM	Effective Spread MM	Effective Spread NMM
	Finals	-	-	-	-	-	-
Romania	Complete	1082	2579	370	447	393	447
	Group	1082	393	370	447	393	447
	Finals	-	-	-	-	-	-
Italy	Complete	2369	1361	949	1310	1028	1363
	Group	1841	1361	681	1310	838	1363
	Finals	2747	n/a	1147	n/a	1167	n/a
France	Complete	1597	1743	465	1710	476	1715
	Group	1597	1743	465	1710	476	1715
	Finals	-	-	-	-	-	-
Croatia	Complete	1489	2332	438	1780	507	1780
	Group	1767	2332	382	1780	393	1780
	Finals	1163	n/a	490	n/a	612	n/a
Poland	Complete	435	824	288	824	289	824
	Group	435	824	288	824	289	824
	Finals	-	-	-	-	-	-
Netherlands	Complete	1408	3177	430	2996	457	3049
	Group	1538	3156	532	2996	563	3049
	Finals	1240	5714	327	n/a	349	n/a
Spain	Complete	1417	774	561	708	586	708
	Group	1584	666	443	444	454	444
	Finals	1259	2423	639	2423	673	2423
Sweden	Complete	1382	2881	371	2348	379	2348
	Group	1382	2881	371	2348	379	2348
	Finals	-	-	-	-	-	-
Turkey	Complete	1262	2066	351	1522	370	1522
	Group	1392	2154	363	1611	380	1611
	Finals	1206	625	346	625	366	625
Portugal	Complete	1207	2375	373	2267	385	2267
	Group	1741	1489	400	723	414	723
	Finals	342	6901	342	6901	351	6901
Russia	Complete	2186	2129	1078	1948	1199	1960
	Group	1094	1941	368	1774	375	1790
	Finals	3003	3636	1609	2727	1816	2727
Average		1403	2477	514	2033	554	2889
p-value		<0.05		<0.05		<0.05	

The results show that spread sizes were significantly smaller in the MM market. This can be expected because the sizes of the spreads quoted by the market maker in the MM market were a part of the designed market maker strategy. But traders accepted these spreads and the market maker quoted new spreads only in case a human trader caused a transaction. Nevertheless, with an equal number of traders in the MM and NMM market, it fostered trading activity.

Table 4.4 shows further basic statistics. The daily number of traded shares was significantly higher in the MM market.

Table 4.4: Descriptive Analysis: The number of transactions per day as well as the average volume traded per day and the average trade size were calculated on a daily basis for the MM and the NMM market.

	# Trades per Day		⌀ Volume per Day	
	MM	NMM	MM	NMM
06 June 2008	6		50	
07 June 2008	107	28	49	81
08 June 2008	34	29	48	80
09 June 2008	159	90	76	83
10 June 2008	169	41	46	108
11 June 2008	119	39	89	84
12 June 2008	861	13	26	168
13 June 2008	36	25	51	86
14 June 2008	301		30	
15 June 2008	251	14	47	59
16 June 2008	51	8	30	38
17 June 2008	336	3	48	230
18 June 2008	574	6	50	103
19 June 2008	206	27	72	356
20 June 2008	211	2	40	15
21 June 2008	170	12	84	87
22 June 2008	195	2	80	26
23 June 2008	76	2	205	53
24 June 2008	62		66	
25 June 2008	36	2	52	15
26 June 2008	230	1	326	200
27 June 2008	23		587	
28 June 2008	82		1473	
29 June 2008	3	2	1067	10
Average	179*	18	195	99

Significance: (*) 1 % level, t-test

4.3 Hypotheses

The research question R1: "Do Information Markets show more trading activity, increased accurate, less error and higher information efficiency utilizing automated market makers?" introduced in Section 1.1 will be evaluated with the following research hypotheses.

1. Trading activity is higher in market maker markets than in non-market maker markets (c.p.)

It can be assumed that automated market making has a positive effect on trading activity and liquidity. The trading activity is measured as number of trades or number of orders per trader as well as the number of transaction per trader per day on average. In order to test the first research hypothesis, the following hypotheses are stated:

H0-1: Trading activity is equal in MM and NMM
H1-1: Trading activity is different in MM and NMM

The results of the investigation of hypothesis 1 are shown in Section 4.4.1.

2. The results in automated market maker markets are more accurate as in non-market maker markets

In the second hypothesis it is investigated if a market maker in Information Markets fosters trading accuracy. To evaluate the second research hypothesis, the following hypotheses are stated:

H0-2: Information Market accuracy is equal in MM and NMM
H1-2: Information Market accuracy is different in MM and NMM

Sections 4.4.2 and 4.4.3 describe the results of hypothesis 2 about the accuracy of both markets.

3. The MM is more information-efficient than the NMM market

The third hypothesis states that the MM is more efficient in information aggregation than the NMM market. This will be evaluated by the comparison of the auto-correlation coefficients for both markets. In general, the auto-correlation coefficient is measured for the efficiency of information aggregation in markets (Schwartz et al. 2006). Moreover, arbitrage trading opportunities indicate if markets are information efficient. Hence, an analysis for arbitrage trading opportunities is also conducted. Therefore, the following hypotheses are stated:

H0-3: Information Market efficiency is equal in MM and NMM
H1-3: Information Market efficiency is different in MM and NMM

The results of hypothesis 3 will be described in Section 4.4.4.

4.4 Experiment Results

In the next sections, the results of the field experiment will be described. Section 4.4.1 introduces an analysis about the market and trading activity. In addition, Section 4.4.2 analyses the forecasting accuracy of both markets compared to several benchmarks whereas Section 4.4.3 describes error measures and price distortions during market runtime. Section 4.4.4 provides results of an information efficiency analysis of the MM and the NMM market.

4.4.1 Market and Trading Activity

Figure 4.8 shows the amount of trades in both markets over time. The number of transactions in the market maker market (MM) was significantly higher at any time.[15] Furthermore, the number of transactions correlates very well to the matches of high interest with alleged top team involvement. Even in the final round, where the trading activity in the non-market maker market (NMM) was extremely low,

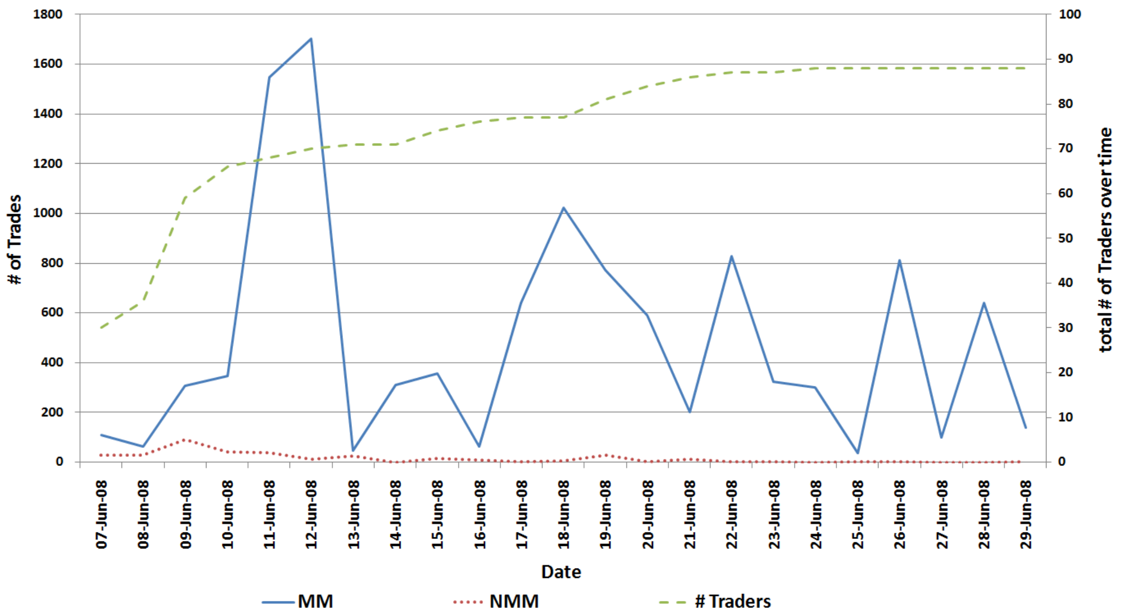


Figure 4.8: Market Activity

several hundreds of trades occurred in the MM market. The green line indicates how the number of traders developed over time.

Another interesting indication for the activity in the MM market is the number of transactions per trader. Figure 4.9 shows the number of transactions per trader in a descending order and a logarithmic scale. The most active trader caused remarkable 1984 transactions in the MM. The second most active trader caused 1267 transactions. In the NMM market, the most active trader caused 155 transactions during 23 trading days followed by the second most active trader who caused 63 transactions.

In order to investigate how the trading activity is distributed over time, Table 4.5 illustrates the trading activity of the 10 most active traders in the MM market. As one can easily see, five[16] of the 10 traders were active till the end of the market. In the final round, the trading activity decreased slightly whereas 62 transactions were observed on the day before the final match (28th of June).

Table 4.6 shows the same data for the NMM market. The results show that many traders traded mostly at the beginning of the market duration. The trading activity decreased constantly towards the end of the group round. A small rise in trading activity was observable at the beginning of the final round, but in the further course, this trading activity also constantly decreased and on 4 out of 11 trading days in the final round no transaction was registered at all. This result is a strong indication for the illiquidity of the NMM market compared to the MM market. In the MM market, not even one day without any trading activity was observed. Moreover, the least active trading day was the day of the final match with two transactions whereas the second least active trading day was two days before the final match with 17 transactions.

[15] t-test, p-value < 0.01

[16] Traders 1, 2, 5, 6 and 8

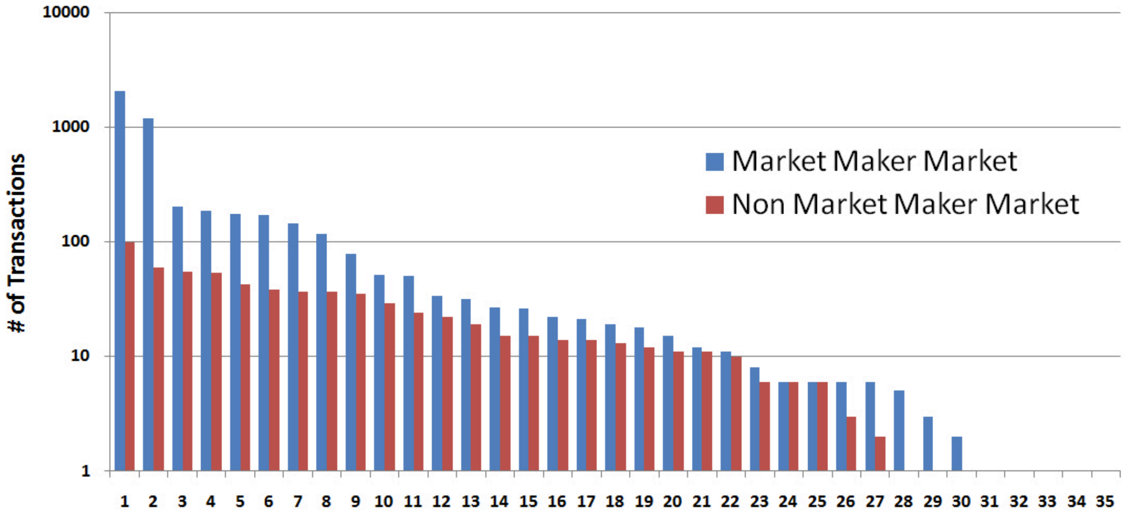


Figure 4.9: Transactions per Trader

In summary, the results presented in this section indicate a dramatic gain in liquidity and trading activity in the MM market compared to the NMM market (cp. Tables 4.8 and 4.9). All results were focused on human involvement which means that only orders and transactions with human involvement either on the buy side or on the sell side were considered. Recapitulating Table 4.2 and Figure 4.8, the results show a strong indication for the higher liquidity in the MM market. The number of transactions with human involvement as well as the market activity were at all times higher in the MM market. Even the number of transactions per trader presented in Tables 4.5 and 4.6 of the ten most active traders shows explicit evidence for the higher trading activity. The indication based on the presented results shows that the MM had significant impact on market liquidity and the MM market was more liquid than the NMM market. The hypothesis H0-1, stated in Section 4.3 can therefore be rejected, that the presence of a MM leads to equal trading activity and equal liquidity (c.p.). In that case, H1-1 can be accepted for this experiment because the MM market showed higher liquidity and therefore more trading activity on a significant level compared to the NMM market. In the next section, the accuracy of both markets is investigated.

4.4.2 Accuracy Comparison

In order to assess the overall accuracy of the two Information Markets, a comparison with two external benchmarks was conducted. For each match during the tournament, betting odds from wetten.de, the last transaction prices in both markets just before a match started and the FIFA world ranking were selected and built the basis for comparison.

Betting odds are perceived as very efficient. In order to avoid monetary losses betting companies having large sums of real money at stake are required to generate accurate forecasts. The incentive to predict accurately is presumably much stronger since in Information Markets there is no real money at stake and only little money at stake in real money Information Markets. Therefore, betting odds were selected to serve as a competitive benchmark.

Table 4.5: Market Statistics per Trader MM: The activity of traders in the MM market is described in detail in this table. For each day during the market duration, the number of trades is calculated for the top 10 of the most active traders (cp. Figure 4.9.)

	Traders										
	1	2	3	4	5	6	7	8	9	10	
07 June 2008	38	62				16		5			121
08 June 2008	17	14						2			33
09 June 2008	31	38		37	17	21	1	15	4	3	167
10 June 2008	20	18	67	22	23	5		4			159
11 June 2008	14	57			29	3		2	15	3	123
12 June 2008	688	72		16	37	22	7	21	13	5	881
13 June 2008	8	17				13	5	1			44
14 June 2008	251	29		22				5			307
15 June 2008	46	135		26		7	46			8	268
16 June 2008	14	19						2		1	36
17 June 2008	195	61		24			14	5			299
18 June 2008	127	376	10	26	2	16	1	15			573
Group Sum	1449	898	77	173	108	103	74	77	32	20	3011
19 June 2008	34	59	31			14	19	3			160
20 June 2008	111	63	16			1	10				201
21 June 2008	48	80	2			1	1				132
22 June 2008	41	78	52			1		7			179
23 June 2008	42	13			4	2		5			66
24 June 2008	3	28	5		16			3			55
25 June 2008		34				1					35
26 June 2008	162	14				3	2	3			184
27 June 2008	7				8	2					17
28 June 2008	61							1			62
29 June 2008								2			2
Finals Sum	509	369	106	0	28	25	32	24	0	0	1093
Total Sum	1958	1267	183	173	136	128	106	101	32	20	4104

The FIFA world ranking is a ranking of all national soccer teams and provides scores for each team based on their success in international matches. The FIFA ranking is updated every month and comprises the outcome of past matches, the importance of past matches, the strength of opponents, regional strength, results in home and away matches as well as the number of goals scored.[17]

During the group phase, draws were possible in each match. Betting odds for draws were always higher at any time than the betting odds for one team to win.[18] In the Information Markets, the last transaction price in case of a draw had to be exactly equal, which is very unlikely and was not the case at any time during the

[17] http://www.fifa.com/worldfootball/ranking/lastranking/gender=m/fullranking.html
[18] The probability for a team to win was therefore always higher than a draw.

Table 4.6: Market Statistics per Trader NMM: The activity of traders in the NMM market is described in detail in this table. For each day during the market duration, the number of trades is calculated for the top 10 of the most active traders (cp. Table 4.9.)

	Traders										
	1	2	3	4	5	6	7	8	9	10	
07 June 2008	9	3		22			8	5	7		54
08 June 2008	3	16		14			4	5	6		48
09 June 2008	72	1		16	16	36	15	4	15	17	192
10 June 2008	13	12		4	13	14	2	8	3	9	78
11 June 2008	17		30		4	3	4		1	4	63
12 June 2008	1	1	2		5			4	2		15
13 June 2008	1	18	11		2		4		2		38
14 June 2008											
15 June 2008	7	1					3				11
16 June 2008			5				1				6
17 June 2008	2	1								1	4
18 June 2008	4				6						10
Group Sum	129	53	48	56	46	53	41	26	36	31	519
19 June 2008	16		8	5	5			13	1		48
20 June 2008	2				3		1			1	7
21 June 2008		7	4				2				13
22 June 2008		1	1				1				3
23 June 2008		2			3						5
24 June 2008											
25 June 2008											
26 June 2008	4										4
27 June 2008											
28 June 2008											
29 June 2008	4										4
Finals Sum	26	10	13	5	11	0	4	13	1	1	84
Total Sum	155	63	61	61	57	53	45	39	37	32	603

experiment. Therefore, matches which ended in a draw were neglected for further investigation.

In the FIFA ranking, teams are listed in a ranking ordered by a score based on success over time. The rank of two teams cannot be equal, thus, a draw could also not be predicted by the FIFA ranking and was neglected for further investigation, too. During the final round, draws were possible after the regular match time. Then, an extra time was played followed by a penalty shootout in case the extra time ended with a draw. For the comparison, the final results were taken including extra times and penalty shoot-outs. Figures 4.10 and 4.11 show exemplary screen shots of betting odds from wetten.de and the FIFA World Ranking.

DATE/TIME	EVENT	1	0	2	SCORE
08.06.2008, 18:00	Österreich - Kroatien	4.45	3.25	1.88	0:1(0:1)
08.06.2008, 20:45	Deutschland - Polen	1.55	3.65	7.00	2:0(1:0)
12.06.2008, 18:00	Kroatien - Deutschland	5.25	3.30	1.75	2:1(1:0)
12.06.2008, 20:45	Österreich - Polen	3.10	3.50	2.20	1:1(0:1)
16.06.2008, 20:45	Polen - Kroatien	3.40	3.30	2.15	0:1(0:0)
16.06.2008, 20:45	Österreich - Deutschland	10.50	4.60	1.33	0:1(0:0)
16.06.2008, 20:45	Polen - Kroatien	2.25	3.65	2.90	0:1(0:0)

Figure 4.10: Betting Odds: wetten.de

Last Updated 04 Jun 2008 Next Release 02 Jul 2008

Ranking	Team	Pts Jun 08	+/- Ranking May 08	+/- Pts May 08
1	Argentina	1559	0	39
2	Brazil	1513	0	-5
3	Italy	1424	0	28
4	Spain	1303	0	-20
5	Germany	1274	0	10
6	Czech Republic	1246	0	2
7	France	1143	0	-62
8	Greece	1133	0	-63
9	England	1123	2	25
10	Netherlands	1111	0	-12
11	Portugal	1094	-2	-37
12	Romania	1069	0	-13

Figure 4.11: FIFA World Ranking

To compile the results of the FIFA World Ranking, the ranking as of June 2008[19] was taken to "replay" the tournament where teams with a higher ranking position were supposed to win the match. In order to compute the hit rate, benchmarks got 1 point if a match was forecasted correctly. Correct in case of betting odds was if the bet for the winning team was lower than for the other team which indicates in turn a higher likelihood. In case of the FIFA ranking, a match was correctly forecasted if one team had a higher ranking position. For both markets, 1 point was assigned if the winning team showed a higher transaction price before the match began. Points of all benchmarks were summarized and a fraction of correct forecasts was computed.[20] Table 4.7 shows the results of the comparison.

Table 4.7: Benchmarks

Method	# of Observations	Hit rate
MM	28	67,86 %
wetten.de	28	67,86 %
FIFA World Ranking	28	60,71 %
NMM	28	53,57 %

[19] http://www.fifa.com/worldfootball/ranking/lastranking/gender=m/fullranking.html#confederation=0&rank=170

[20] This method is adapted from Luckner (2008), where a similar comparison was conducted during the FIFA World Cup 2006.

The comparison of the MM market, the NMM market, the FIFA World Ranking as well a betting odds from wetten.de shows that the MM market performed equally appropriate to betting odds from wetten.de[21] with an accuracy of 67,9 % followed by the results of the FIFA Ranking with 60,7 % and the NMM market with 53,6 %. The results of the comparison with external benchmarks show that the MM market was as accurate as the betting odds from wetten.de. Luckner (2008) conducted an experiment for the FIFA Soccer World Championship in 2006 and showed that the results of the Information Market were slightly less accurate than the benchmark of the betting odds from wetten.de, which were the more accurate predictor during that tournament.

The MM as well as the NMM market were supposed to forecast the teams reaching the final round in a first step as well as the winner of the tournament in a second step. A perfect forecast would have been if at the first trading day exactly eight teams showed transaction prices of about 100 currency units whereas the others would have been traded at about 0 currency units. Transaction prices in a "winner-takes-all" contract represent the likelihood about the outcome of the underlying event. Therefore, the comparison to benchmarks for single matches, e.g., betting odds, is not exactly about the same forecasting objective. The markets were supposed to forecast a total outcome of parts of a tournament whereas betting odds and the FIFA world ranking were supposed to forecast single matches. Hence, the comparison described above gives only a weak indication of the overall accuracy of the MM and NMM market against the two benchmarks. In order to provide stronger evidence, another approach was conducted. In the following, draws were regarded in betting odds. The overall objective was to generate a group ranking based on the quotes from bookmakers where the consideration of draws is necessary for the quality of the results of betting odds. First, the betting odds were transformed into probabilities for win, draw and lose for each team in each match. As seen in Figure 4.10, quotes were available for both teams. The quotes can be transformed as follows.

$$\text{Probability} = \frac{1}{\text{Quote}} * 100 \tag{4.3}$$

In case of the first row in Figure 4.10 which was Austria vs. Croatia, the quotes were 4.45, 3.25, 1.88. Thus, the probabilities for that match were:

1. Austria wins: $\frac{1}{4.45} * 100 = 22.47\,\%$
2. Draw: $\frac{1}{3.25} * 100 = 30.77\,\%$
3. Austria loses: $\frac{1}{1.88} * 100 = 53.19\,\%$

Summarizing all probabilities, one may notice that they sum up to 106.43 % which is more than 100 %. This is because the bookmaker sets his quotes in order to make a profit. Usually, bookmakers set the quotes of higher quotes/lower probabilities[22] a

[21] wetten.de moved to digibet.com for internationalization https://www.digibet.com/?lang=01

[22] In this case Austria wins (Quote: 4.45, Probability: 22.47 %) and draw (Quote: 3.25, Probability: 30.77 %).

little bit lower to attract traders to buy lower quotes and bet on less likely outcomes. Therefore, the profit of bookmakers cannot be differentiated in quotes because it is the bookmakers secret how to set quotes. For the comparison in this work the profits of bookmakers can be neglected because they do not change the overall outcome based on the quotes. For the computation of the accuracy in this work, it is important to get the probabilites to process the next step which ist the generation of group rankings based on the probabilities computed via Equation (4.3) for all matches. The profit of bookmakers is unknown to the public. Therefore, it is not possible to separate them in order to compute probabilities without these profits. As a test, the probabilities without these profits were computed whereby the 6.43 % were equally assigned in order to have the sum of probabilities of all three outcomes summing up to 100 %. The results concerning the outcome of the quotes do not differ and therefore, the probabilities are further computed with the available quotes incl. the profit of bookmakers.

Based on the computed probabilities, a ranking for each group can be compiled. Therefore, probabilities were weighted with the reward a team gets for winning or a draw. For example, if a team wins a match, it gets three points in the group ranking. For a draw, teams receive one point and zero points for losing a match. The winning probability for Austria vs. Croatia was 22.47 % and the probability for a draw was 30.77 %. Altogether, the weighted results for that match summarize to $3 * 0.2247 + 1 * 0.3077 + 0 = 0.9818$. For that match, 0.98 points can be expected for Austria according to betting odds. If this is conducted for all matches and summarized for one group, a ranking ordered by the sum of weighted probabilities for the expected points $E(p)$ during the group phase can be compiled. Afterwards, the linear distance can be measured to the real outcome of the team ranks in each group. The linear distance is also calculated for the MM and the NMM market according to transaction prices before the matches were kicked-off. The group ranking was also conducted for the FIFA ranking according to the rank of teams in the FIFA ranking. Teams with a higher rank were supposed to win the matches against lower ranked teams. The sum of all distances per benchmark indicates the accuracy for the forecast of team rankings after the group phase. The lower the sum of the distance is, the better the accuracy of the method. The distance was calculated for the two group winners, which was the forecast objective for the MM and NMM market, as well as the overall group ranking. Table 4.8 shows the results. The linear distance is denoted as d_i, wheras a lower d_i indicates more accuracy.

The results show that the MM market forecasted the group results more accurate compared to wetten.de. The sum of the linear distances is lower than every other benchmark.

During the final round, a ranking of the eight teams cannot be conducted because if one team is predicted to move to the next stage and loses the match, it drops out of the tournament. Otherwise, in case the team is predicted to lose the next match and it wins, the ranking would be not representative. Table 4.9 therefore shows the evolution of transaction prices on each trading day during the final round before a match was kicked-off. The highest transaction price indicates the aggregated estimation which team will win the tournament, which is highlighted in bold letters.

Table 4.8: Accuracy of Benchmarks: For each group, the group ranking was calculated based on quotes from wetten.de, last transaction prices from the MM and NMM market and the FIFA ranking. The differences to the outcomes are measured with a linear distance. For example, a distance of 1 indicates that the accuracy for that team differs by one rank. $E(p)$ denotes the expected group point per team derived from betting odds. d_i denotes the difference to the observed group per team.

Group	Official Result	$E(p)$	wetten.de	d_i	MM	d_i	NMM	d_i	FIFA	d_i
A	Portugal	5,61	Portugal	0	Portugal	0	Portugal	0	Czech Republic	2
	Turkey	4,41	Switzerland	2	Czech Republic	1	Switzerland	2	Portugal	1
	Czech Republic	3,95	Czech Republic	0	Turkey	1	Czech Republic	0	Turkey	1
	Switzerland	3,31	Turkey	2	Switzerland	0	Turkey	2	Switzerland	0
B	Croatia	6,69	Germany	1	Croatia	0	Germany	1	Germany	1
	Germany	4,08	Croatia	1	Germany	0	Croatia	1	Croatia	1
	Austria	3,53	Poland	1	Austria	0	Austria	0	Poland	1
	Poland	2,73	Austria	1	Poland	0	Poland	0	Austria	1
C	Netherlands	5,11	Italy	1	Netherlands	0	Netherlands	0	Italy	1
	Italy	4,74	Netherlands	1	Romania	1	France	2	France	2
	Romania	4,74	France	1	Italy	1	Italy	1	Netherlands	2
	France	2,74	Romania	1	France	0	Romania	1	Romania	1
D	Spain	6,11	Spain	0	Spain	0	Sweden	2	Spain	0
	Russia	4,07	Russia	0	Russia	0	Greece	2	Greece	2
	Sweden	3,69	Sweden	0	Sweden	0	Spain	2	Russia	1
	Greece	3,44	Greece	0	Greece	0	Russia	2	Sweden	1
Group Winners Rank ($\sum d_i$)				6		2		10		10
Total Group Rank ($\sum d_i$)				12		4		18		18

Table 4.9: Final Round Trading Prices MM

	19 June	20 June	21 June	22 June	25 June	26 June	29 June
Germany	2,7	30,0	33	**64,8**	**70**	**85**	**55**
Spain	12,4	10,3	10,3	13	16,7	10	40
Russia	1,8	1,5	3,5	6,75	6	7	
Turkey	2,5	2,0	4	2,4	5,6		
Italy	4,8	5,2	11,2	10			
Netherlands	**37,6**	**31,0**	**44,8**				
Croatia	7,75	6,2					
Portugal	35						

From the 19th to the 21st of June the Netherlands were supposed to win the tournament in the MM market. After the Netherlands dropped out of the tournament, Germany was supposed to win. Germany lost the final match against Spain 0:1. The results from the NMM market cannot be computed because during the final round, there were too few transactions observable in order to compute sensible results. Luckner (2008) investigated the home bias of traders in order to explain that traders mainly trade shares of their national teams. Furthermore, they tend to overestimate the likelihood of success for their national teams. In the MM market, mainly German traders were active and therefore it seems that they were subject to the home bias effect and overestimated the likelihood that Germany would win the tournament.

According to Table 4.7, the MM market outperformed the NMM by 12,9 %. In addition, the results in Table 4.8 show that the MM market forecasted the group results more accurate than the NMM market. The linear distance was 2 vs. 10 for the forecast of group winners and 4 vs. 18 for the forecast of the total group ranking. The hypothesis H0-2, that the MM and NMM markets show equal accuracy can, therefore, be rejected.[23] Furthermore, the FIFA world ranking was also outperformed by both measures, the hitrate and the group ranking forecast.

The accuracy of the MM market compared to the betting odds from wetten.de was equal with the first measure (cp. Table 4.7). In the second measure, the MM market outperformed the betting odds in the group winners' rank as well as the total group ranking at a significance level of 1 %.

4.4.3 Error Measures

In order to measure the forecasting error for the MM and the NMM market, the average transaction price for each stock was computed for each trading day according to the following equation.

$$\frac{1}{N_i}\sum_{j=1}^{N_i} p_j^i\,(x)\,, \forall i \in I = (1,..,32), N \in \mathbb{N}_0^+ \tag{4.4}$$

Equation (4.4) computes the average price for each stock where p is the price of each transaction in each stock i. I denotes the number of all stocks, N denotes the number of transactions in each stock i whereas j denotes the trading day.

[23]Significant to the 1 % level.

The mean absolute error (MAE) indicates how accurate both markets were during the first 12 days of trading, which was the group phase of the tournament.[24] Equation (4.5) illustrated the formula for the computation of the MAE, where $\widehat{p_j}$ denotes the payout value and p the market price.

$$MAE = \frac{1}{N}\sum_{j=1}^{N}|\widehat{p_j} - p_j| = \frac{1}{N}\sum_{j=1}^{N}|e_j| \tag{4.5}$$

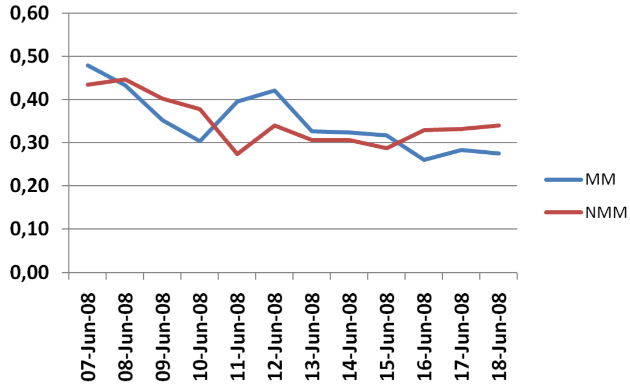
The MAE was ex post calculated based on the final outcome of the group phase for each team. For each day, the rank of each team was calculated ordered by average transaction prices per day and then compared to the real outcome. It could be expected, that the MAE would decrease in the course of the tournament as more information was available. Figure 4.12 shows the market error over time.[25]

Interestingly, on the 5th and 6th trading day a distortion of transaction prices was observed in the MM market (Figure 4.12(a)). A distortion of transaction prices was detected on the 5th trading day in the MM market because one trader tried to buy shares of Germany contracts for 5.000 currency units and sold it to himself several minutes later. This caused a reaction by the market maker trying to adjust other prices to lower levels. Therefore, prices showed a higher error rate. Several hours later, transaction prices came back to a normal level by transactions of other traders. If the price distortion is neglected and transaction prices are also neglected after it could be determined that a team has reached the finals or dropped out of the tournament, the error rate is significantly lower in the MM market. Figure 4.12(b) shows the adjusted transaction prices without the distortion of transaction prices.

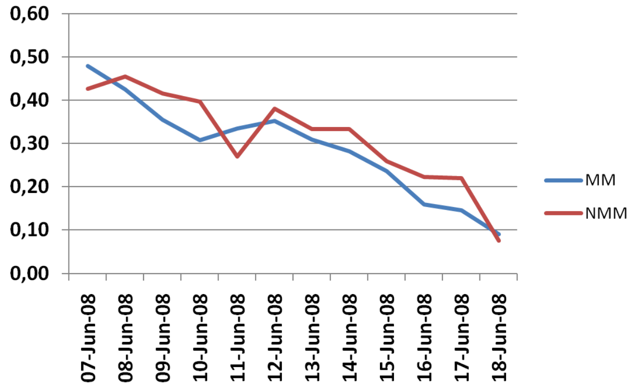
In Figure 4.12(a), transaction prices were taken as they were during the market duration. Sometimes a team could already have reached the final round before they had played their third match during the group phase because they won the first two matches. From that point in time, the price of the contract representing that team should be 100 because the information that this team reached the final round was publicly available. But traders did not integrate this information in prices appropriate. Moreover, this can be considered as an information inefficiency in the market. In Figure 4.12(b), these errors were adjusted and as soon as a team was identified to reach the final round or drop the market, a transaction price of 0 in case of a drop or 100 in case of reaching the final round was available as public information and therefore reducing the error. Since traders did not integrated stock prices of successful teams correctly, the distortions can be eliminated because it makes no sense to trade events which are already public information. This experience will help to design further markets which design is capable of instantly avoiding such situations and pay out shares if necessary. The results from the MM market in Figure 4.12(a) are not significant, whereas the results in Figure 4.12(b), where the prices were adjusted based on public information are significant to the 10 % level. This indicates that the MM market shows significantly less forecasting error than

[24] The error calculation was based on the group phase of the tournament because in the final round the trading activity in the NMM was too low to compare it to the MM.

[25] The evolution of undistorted market errors for the MM and the NMM market are shown in detail in Appendix A, Table A.1.



(a) Error Measures - distorted



(b) Error Measures - undistorted, adjusted

Figure 4.12: Error Measurement

the NMM market. The overall results presented in this section support the rejection of hypothesis H0-2 which was previously rejected during the investigation of forecast accuracy in Section 4.4.2.

4.4.4 Information Efficiency

The information efficiency of markets describes how efficiently a market integrates public as well as private information (cp. also Section 3.1.1). In general, efficiency cannot be measured with one parameter, it depends on a set of data and the market characteristics as shown in Table 4.2. In scientific literature, one of the characteristics of efficient markets is the correlation of trade prices (Harris 2003; Schwartz et al. 2006). It is assumed that the sequence of trade prices should follow a random walk. This means that it is not predictable if the next transaction will be buy or sell (Schwartz et al. 2006). If at any time the current trade price reflects the full information, then the price should not change. If so, the stock's price is no appropriate reflection of the current information. Regarding the efficient market hypothesis, the stock price should only change once new information is available to traders and they provide their interpretation of it in the market. Information has to be "new" otherwise it would have been already integrated in the current stock price as public information. Therefore, the effect of new information cannot be predicted since one cannot assume which information will occur and, thus, the stock price cannot change. The stock price evolution must, therefore, follow a random walk and consecutive stock prices should not correlate to prior ones (Schwartz et al. 2006).

In order to measure the efficiency of markets, correlation patterns in stock prices indicate if stock prices are related (cp. also Section 3.3.4). There are two forms of correlation patterns, inter-temporal correlation patterns and serial cross correlation patterns. Inter-temporal correlations are also referred to *auto-correlation* or *serial-correlation* and can be positive or negative. In the first case, a sequence of buy trades raises the price, hence, the trading sequence is positively auto-correlated. In the second case, prices tend to decrease sequentially via sell trades.[26] The more random this sequence is, the less auto-correlation will be observable. For example, if several buy trades follow buy trades, a high auto-correlation is observable. Auto-correlation measures the dependency of the sequence of trades. If a sequence of trades is correlated, several traders relate their transaction decision based on the observation of what happened in the trade before. In contrast, serial cross-correlations are related to the returns of two or more different stocks and indicate if the advent of new information has an asynchronous effect on different stocks. In financial stock markets, the theoretical optimum of a random walk in stock prices cannot be reached because stock prices are always slightly correlated due to imperfections in the price discovery process (Schwartz et al. 2006).

For the analysis of the information efficiency of the MM and NMM markets, the first order auto-correlation indicates the information efficiency which can be compared to the MM and the NMM market. The analysis of the final round has to be discarded because there was insufficient trading activity in the NMM. Therefore, only the group phase can be used for the following analysis.

In order to measure the first order auto-correlation of the field experiment data, the sequence of buy and sell transactions was analyzed for each contract in the MM and NMM. Buy transactions were tagged with (1) and sell transactions were tagged with (-1). Then the auto-correlation was computed on that sequence for both markets. Afterwards, the difference between the MM and the NMM market was calculated following Equation (4.6) to show the improvement (*Diff*) of the MM to the NMM market. Table 4.10 shows the results.

$$\textit{Diff} = |\mathrm{NMM}| - |\mathrm{MM}| \tag{4.6}$$

The auto-correlation coefficient ranges between (-1) and (1). Therefore, negative values can appear if a sequence of sell transactions (-1) is dominant. In theory, the optimal value should be 0. Thus, values close to 0 indicate a higher level of market efficiency (Schwartz et al. 2006). Summing up each squares[27] ($\sum x^2$) the MM market shows a lower auto-correlation coefficient by 1.03. Therefore, the MM market integrated information more efficiently than the NMM market during the group phase. Some values show an auto-correlation coefficient of slightly more than

[26] For a discussion about possible reasons for positive/negative auto-correlation refer to Schwartz et al. (2006).

[27] An average value is not applicable in this case because the auto-correlation coefficient ranges between (-1) and (1).

Table 4.10: Auto-Correlation: The auto-correlation coefficient is calculated based on the sequence of buy/sell transactions. Buy trades were assigned (+1) and sell trades were assigned (-1). For each contract, the sequence of transactions (buy/sell) is analyzed for first order auto-correlation. The difference (*Diff*) indicates the improvement against the other market. Positive values indicate the lower auto-correlation coefficient in the MM market whereas negative values indicate a lower auto-correlation coefficient in the NMM market.

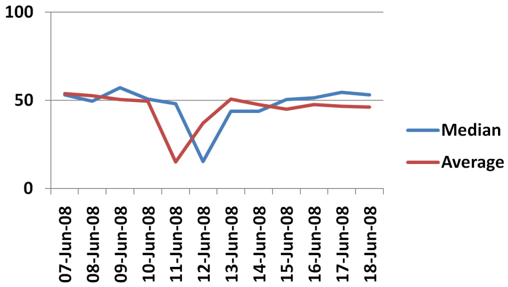
Contracts	MM	NMM	*Diff*
Austria	-0.23	0.47	0.23
Switzerland	0.46	0.84	0.37
Germany	0.04	-0.09	0.05
Greece	0.50	-0.15	-0.34
Czech Republic	0.25	-0.25	0.00
Romania	0.29	-0.08	-0.21
Italy	0.28	0.33	0.05
France	0.20	0.20	0.00
Croatia	0.24	0.03	-0.21
Poland	0.44	1.00	0.56
Netherlands	0.09	0.15	0.07
Spain	0.16	0.03	-0.13
Sweden	0.41	-0.18	-0.23
Turkey	0.17	0.19	0.01
Portugal	0.11	0.36	0.25
Russia	0.31	0.10	-0.21
$\sum x^2$	1.37	2.40	

0.4 at maximum, which is similar to those of financial markets. Most of them are between 0 and 0.4 which indicates that the MM market integrated information efficiently.[28] Column *Diff* indicates which market was more efficient. For example, the MM market "beats" the NMM market in contract 1 by 0.23 and was therefore *more* information efficient. If the *Diff* shows a positive sign, the MM market was more efficient and vice versa.

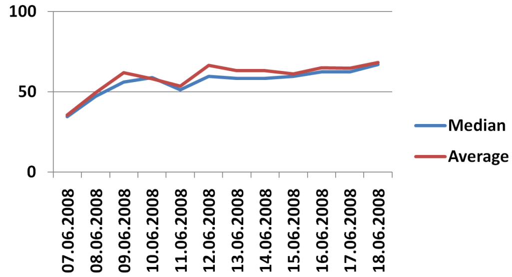
Another characteristic of efficient markets are arbitrage trading opportunities. If arbitrage opportunities are exploitable, markets lack information efficiency. Shares are over- or undervalued and can therefore be bought in the market and sold in another market riskless and vice versa. In order to investigate the arbitrage opportunities in the MM and the NMM market, Figure 4.13 shows the aggregated transaction prices per day over time. The better the lines adapt to 50 currency units, the less arbitrage opportunities are available in general.

On the 5$^{\text{th}}$ trading day the MM market showed an unforeseen behavior. The arbitrage opportunities were extremely high. This is because one trader tried to buy shares at a price of 5.000 currency units and sold them to himself for 5.001

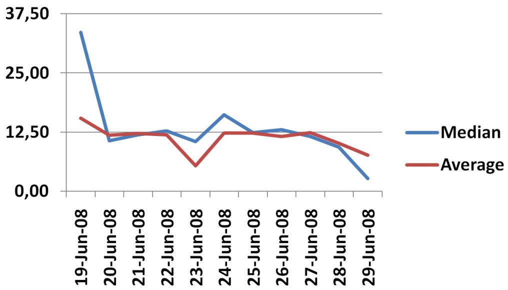
[28]It can be assumed that the mentioned imperfections and auto-correlation theory, which are known in financial markets, are transferable to Information Markets.



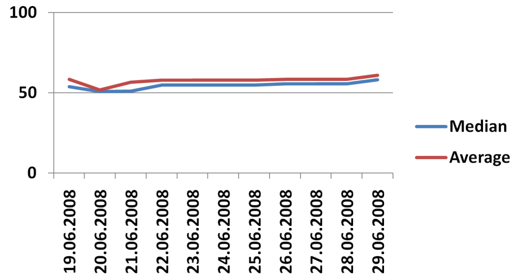
(a) MM Group Phase Arbitrage Opportunity



(b) NMM Group Phase Arbitrage Opportunity



(c) MM Finals Arbitrage Opportunity



(d) NMM Finals Arbitrage Opportunity

Figure 4.13: Arbitrage Opportunities during Group and Final Round

currency units. This caused a reaction by the market maker trying to adjust prices to the new situation. Therefore, the accuracy dropped on that day as arbitrage opportunities were available. It took only several hours until prices came back to a normal level. Nevertheless, this issue was causal for the MM market not to show significantly less arbitrage opportunities during the group phase compared to the NMM market. In the final round, the results are significant to the 1 % level.

In order to report the results without the price distortion, the irrational transaction price of 5.000 was neglected and a new analysis was conducted. Overall, without the price distortions on the 5th trading day, the results show significance to the 1 % level. This indicates that the MM market would have shown less arbitrage trading opportunities than the NMM market. Figure 4.14 shows the adjusted chart in contrast to Figure 4.13(a).

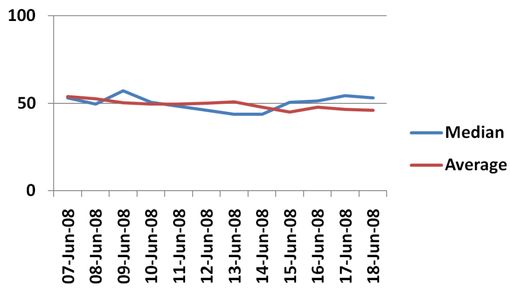


Figure 4.14: Arbitrage Opportunities - undistorted

In order to show the difference of both markets, Table 4.11 summarizes the results.

Table 4.11: Arbitrage Opportunities Comparison: The average arbitrage opportunity was calculated for the group phase as well as the final round. The calculations are conducted with the median as well as the average transaction prices and represent the sum of all prices divided by the sum of all payouts. In the group phase, the optimal value should have been 50, during the finals, the optimal value should have been 12.5. Only the adjusted MM market results without the price distortions shows significantly lower arbitrage opportunities to the 1 % level.

	Group Phase		Finals	
	Median	Average	Median	Average
MM	47,60	45,22	13,15	11,20
MM (undistorted)	50,16	49,18	./.	./.
NMM	56,34	59,12	54,45	57,65

The results in Table 4.11 are not significantly better for the MM market during the group phase due to the price distortions and the consequent arbitrage opportunities. Nevertheless, the results show significance to the 1 % level in the final round. If the effect of the price distortion is neglected, the results show significance at the 1 % level during the group phase. This is a strong indication that the MM market showed less arbitrage opportunities and was therefore more efficient in information aggregation than the NMM market. Altogether, hypothesis H0-3 can be rejected.

4.5 Conclusion

In this chapter, the effect of automated market making on trading activity, accuracy and market efficiency was investigated with a field experiment. Two identical markets were set up for the European Soccer Championship in 2008 where one market employed an automated market maker mechanism and the other one did not. Both markets showed an equal number of active participants and were functionally identical.

The results show that the trading activity was significantly higher in the MM market which can be explained by the continuous trading opportunity provided by the automated market maker, it animated human traders to update their beliefs about the soccer matches more often so they could provide their expectations to the market immediately. Besides, the analysis of the trading activity showed that every trader did significantly more transactions in the MM market.

Furthermore, the presence of an automated market maker mechanism seemed to cause significant benefits in market liquidity through the attraction of human traders which caused a gain in market accuracy as well as a decrease in forecasting error as shown in Sections 4.4.2 and 4.4.3. Compared to the NMM market, the MM market was equally accurate as betting odds from wetten.de and more accurate than a benchmark based on the FIFA World Ranking. In addition, the accuracy in forecasting the outcome of the group ranks after the group phase was extremely accurate in the MM market and outperformed the forecasts derived from betting odds as well as those of the NMM market and the FIFA ranking.

The forecasting error in both markets was on an equal level at the beginning of the group phase. A price distortion on the 5^{th} trading day caused by a human trader raised the forecasting error in the MM market so that the error measures for both markets were nearly the same. After adjusting the data and neglecting the price distortion, which can be seen as an obvious manipulation attempt or misunderstood trading rules, the error measures decreased in the MM market to a significant level. The error in the MM market would have been definitely lower than the error in the NMM market which gives further evidence about the overall accuracy of the MM market compared to the NMM market.

Regarding the information efficiency described in Section 4.4.4, the MM market integrated information more efficient than the NMM market. The results from an analysis of the sequence of trading prices show that trading prices in the MM market were less auto-correlated than transaction prices in the NMM market. This indicates that the MM market was more efficient. Furthermore, an investigation of arbitrage opportunities in both markets provides evidence that the MM market offered significantly less arbitrage opportunities. This is a strong indication that the MM market shows increased information efficiency. Altogether, Table 4.12 summarizes the results of this chapter and highlights the characteristics of both markets during the conducted field experiments.

Table 4.12: Summary of Results

Investigation	Measure	MM market	NMM market	Significance
Trading Activity	Total # of trades	●	◐	●
	Activity of traders	●	◐	●
Accuracy	Hit rate	●	◐	○
	Group phase forecast	●	◐	●
Error	MAE	●	●	○
	MAE w/o distortions	◐	●	●
Information Efficiency	Auto-Correlation	◐	●	○
	Arbitrage opportunities	◐	●	●

● fulfilled/satisfied, ◐ partly fulfilled/satisfied, ○ not fulfilled/not satisfied

Altogether, the main experience from this field experiment is that traders distorted trading prices in some contracts which can be avoided by regulative arrangements in the market system. For example, the maximum trade price should be bounded by 100 currency units that traders have no possibility to overprice contracts. Even if they would find a counterpart, this can be denoted as irrational behavior since the maximum payout was 100 currency units.

Furthermore, it has to be investigated if a situation can occur in which an early close of contracts and payout should be conducted. During the group phase, a few teams reached the final round or dropped out of the tournament prior to the regular payout date. During that time, transaction prices do not add further information to the market which opens opportunities for gambling and manipulation. These situations should be identified carefully and appropriate mechanisms have to be developed in order to avoid these situations.

Nevertheless, with adjusted or neglected distortions mentioned above, the MM market significantly showed an increased accuracy, more trading activity as well as increased information efficiency compared to the NMM market. Since the number of traders was equal in both markets, the results in nearly all measures were superior in the MM market which can be traced back to the employment of an automated market maker mechanism, which was the only difference between both markets. Therefore, the usage of automated market maker mechanisms is favorably in small markets. Interestingly, the MM market was able to motivate about 6-8 traders to constantly update their expectations and beliefs during the course of the tournament for about three weeks. The relative low incentive of winning a price worth 125 € raffled in each market worked surprisingly well. This shows that people participated not only to win the price (which was bound to a winning probability) but rather from other motives which are briefly explained in Section 3.1.2. The time they were willing to invest to update their expectations nearly every day for a duration of three weeks is astonishing for the relative low incentive. Besides, some of them may have perceived trading in the markets as fun and entertaining.

In summary, the main objective of this field experiment was to investigate the effect of automated market making on the trading activity, forecasting accuracy and information efficiency in a well understood field of application where Information Markets constantly deliver very accurate results. As means to an end, the promising results presented in this chapter provide valuable experience for the development of small-sized Information Markets, for instance, innovation assessment. In innovation contexts, low trading activity and small markets are more likely as in Information Markets in contexts of public interest. Thus, a field experiment for innovation assessment in a company, which is described in the next chapter, was implemented using the valuable experience shown in this chapter.

5 Enterprise Information Markets for Innovation Assessment

When companies noticed the predictive power of Information Markets, they began to launch first prototypes and experiments for internal usage. Once they realized the advantages, they adapted them for internal market analysis, forecasting of sales figures, operations planning as well as project management (Ortner 1998; Eliashberg et al. 2000; Gruca 2000; Plott 2000; Spann 2002; Spann and Skiera 2004; Dahan et al. 2007; Tetlock 2008; Cowgill et al. 2009). For example, companies like Google, Intel or HP are using internal Information Markets. Yet, Information Markets have not become an established part of companies forecasting strategy.

Despite the sporadic usage of Information Markets for the management of projects, they often experience trouble due to several reasons. Jørgensen et al. (2008) provide facts and challenges based on a comprehensive survey among 1.500 practitioners worldwide in order to investigate the reasons of project failures.[1] An interesting figure is the high number of troubled projects, which did not reach their goals or were stopped. Figure 5.1 shows the results of the survey regarding the project success rate in companies. In total, 41 % of the projects fully met their objectives. In contrast, 59 % were troubled whereas 15 % out of these 59 % missed their goals or were stopped.

Jørgensen et al. (2008) introduce several challenges, which have to be tackled in order to avoid project failures. In Figure 5.2, the three major challenges are the “changing mindset and attitudes” followed by the “cooperate culture” and the “complexity of projects” with 58 %, 49 % and 35 % respectively. Interestingly, three other challenges are mentioned, which can be addressed with the contribution of this work:

- Lack of commitment of higher management (32 %)

[1]The survey covered 1.532 organizations of all sizes, balances around the globe and across industries. In total, 21 industries, whereby 14 % companies employed more than 100.000 employees and 22 % had less than 1.000 employees.

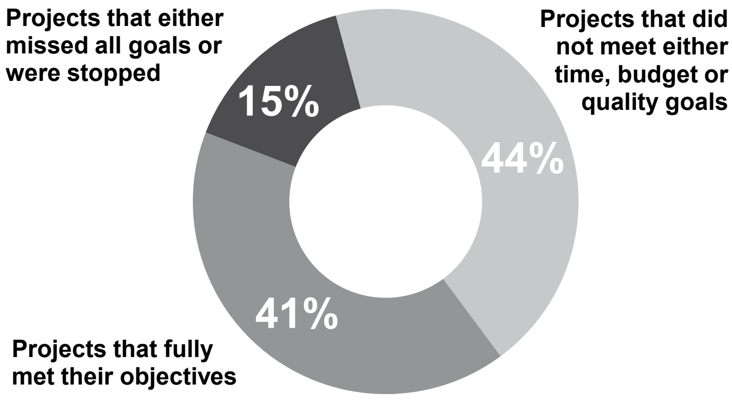


Figure 5.1: Success Rate in Change Projects
Adapted from Jørgensen et al. (2008)

- Lack of transparency because of missing or wrong information (18 %)
- Lack of motivation of involved employees (16 %)

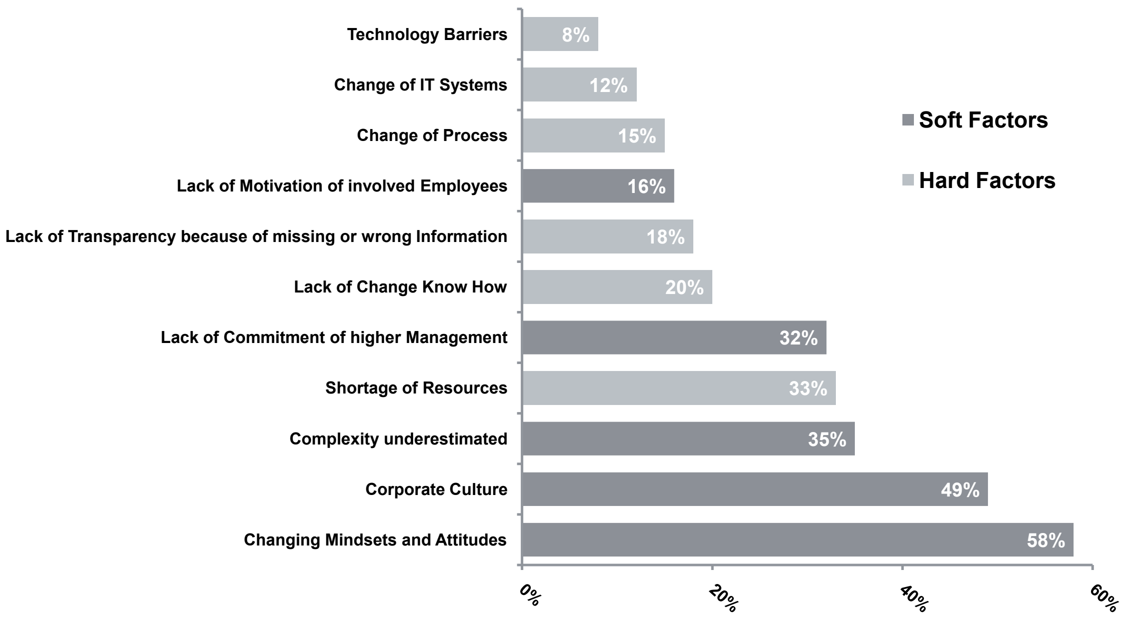


Figure 5.2: Challenges in Change Projects
Adapted from Jørgensen et al. (2008)

Enterprise Information Markets are intended to be used by a representative fraction of a relevant group. In case of innovation contexts, employees, for instance of the sales department, or customers are valuable sources of information. Information Markets can be a method to mitigate some of the challenges like the commitment of management or information transparency. In an Information Market, available information becomes consolidated and therefore, information becomes transparent. Even if the higher management takes part in Information Markets, it shows its commitment through the usage of the market system just like regular employees.

These are two examples of how several problems in change management can be addressed with Information Markets. Information Markets cannot surely solve any challenges mentioned in Figure 5.2 – but they may provide a contribution in order to tackle some of them. In the following, a field experiment in an enterprise innovation context is described where challenges, mentioned above, are addressed.

5.1 The EnBW Information Market

Service Innovation is a crucial activity for companies in order to maintain business success over time. Section 2.3 outlined challenges as well as requirements to be innovative in intra- as well as inter-organizational contexts. Strategic decisions about innovations are important tasks and innovation strategies are directly linked to the business strategy as mentioned in Section 2.1. Depending on the type of innovation, an appropriate and comprehensive decision making process should be applied to avoid trouble during the implementation of innovations as well as to reduce avoidable costs (Dannenberg and Burgard 2007). As mentioned in Sections 2 and 3.3.1, employees, customers, consultants or independent experts can be considered as participants in Information Markets. A difficulty in decision making in innovations contexts is that decisions have to be made even under high risk, high investment costs or uncertainty. Therefore, to avoid overlooking crucial aspects in decision making about innovations, employees are a valuable source to be considered (cp. Section 3.4.3). In order to analyze the application of Information Markets with employees, a field experiment was conducted at EnBW, which is one of the biggest electricity suppliers in Germany. In the experiment, an Information Market was used to aggregate estimations about innovation proposals.

5.1.1 Experiment Design

In the remainder of the experiment, the objective of the innovation workshop as well as the field experiment design was discussed with decision makers prior to the workshop. The innovation workshop in March 2009 was held the 3$^{\text{rd}}$ time and the experience of the executives is that employees are interested and contribute their expectation and knowledge. The workshop's objective was to provide a mixture of presentations about new technologies concerning internal processes in order to foster attendants' creativity. In a second step, they developed innovation proposals aiming to improve internal processes.

After the 1$^{\text{st}}$ day, attendees had a comprehensive overview about the introduced topics and technologies. These topics and technologies ranging from interactive social technologies to devices for power management were identified by company representatives prior to the workshop. An initial collection of technologies was gathered by an agency and the 12 most interesting ones were selected to be presented in the presentation slots.

On the 2$^{\text{nd}}$ day, attendees had the opportunity to discuss their ideas with each other in groups in order to further develop and improve them. After 30 minutes, groups were mixed up so that everybody could discuss with different people to get feedback. Once promising ideas were ready, attendees submitted them. On the 2$^{\text{nd}}$ day, about 80 ideas were submitted.

The company noticed during the two days workshop, that attendants were very interested in further developing their ideas and therefore, they supported discussions and further developments with a company internal wiki software in their intranet. Attendees had the possibility to review and discuss their innovations in an online discussion forum. After a few weeks of improvement and discussion, 12 ideas were ready to be assessed via an Information Market for employees, an Information Market for experts as well as a questionnaire for decision makers. After the experiment, the results of the three methods were compared. Table 5.1 gives an overview of the 12 innovation alternatives.[2]

Table 5.1: Products in the EIM

ID	Name (Original)	Name (Translated in English)
1	Twitterinfo	Twitterinfo
2	MEREGIO-Plattform	MEREGIO Platform
3	Heim-Automation	Home Automation
4	Parallele Dokumentenbearbeitung	Parallel Document Processing
5	Intelligente Terminplanung	Intelligent Calendar Management
6	Web 2.0 Plakate	Web 2.0 Poster
7	Digitalisieren von Visitenkarten	Digitizing Business Cards
8	xing@enbw.com	xing@enbw.com
9	New Contact Networking	New Contact Networking
10	All in One	All in One
11	Geräteinventar	Hardware Inventory
12	mobile Zählererfassung	Mobile Metering

As described in Section 3.4.3, these alternatives can be assessed by employees via an internal Information Market. So far, the experience of earlier workshops was that participants were very cooperative and interested during the workshop, but there was no adequate method to keep them involved in the innovation context after the workshop. Therefore, it should be evaluated, if workshop participants can be kept in the innovation process via the employment of an Information Market. Participants of the innovation workshop were invited to join the Innovation Market and to keep on the innovation topics several weeks after the workshop.

The market was online available from the 4th of May 2009 till the 12th of June 2009. Furthermore, compared to a regular financial exchange, the market was available 24 hours, 7 days a week. In total, ca. 110 people joined the innovation workshop and everybody received an anonymous account as well as a password to join the market. The participants were supposed to trade stocks representing innovation alternatives (Table 5.1) in order to rank them according to their personal expectation about the overall benefit for the company. The representing stocks were initially issued for each user account as well as an initial amount of money. Each account was endowed with 100 shares of each stock and 100.000 virtual currency units. The market endowed users initially, that participants were able to trade immediately

[2]In the following, the English names of innovation alternatives are used. In the field experiment, the original names were in German language. In Appendix B, Figures B.13 - B.19 show screenshots of the market system where the original names are used. Refer to Table 5.1 for translation.

in each stock and did not have to arrange their initial depot themselves. Traders were supposed to interpret available information related to the benefits and the feasibility of innovation alternatives and to provide it in the market. Information may get available via internal news channels, company wide information systems or discussions with colleagues.

In addition, an automated market maker mechanism was used in the market based on the results showed in Chapter 4. Since it was expected that only a few traders would register to the market system, the automated market maker mechanism should provide continuous trading capabilities and, thus, improve market activity, accuracy and efficiency. The trading strategy of it slightly differed to the strategy described in Section 4.1.2. The difference was the determination of how many shares it offers. In contrast to the strategy used in Section 4.1.2, it draws a random number out of an interval[3] and did not used a fixed number of shares. Altogether, the application of the automated market maker mechanism was intended to improve the market quality in this field experiment as well, as already demonstrated in Chapter 4.

As described in Section 3.2, the strategy of selling and buying shares depends on the participant's individual expectation of the attractiveness of the underlying innovation. If traders think that an innovation is overvalued compared to another innovation alternative, which in their mind is of minor attractiveness, they were supposed to sell shares. Vice versa, if an innovation alternative is undervalued in their opinion, they are supposed to buy it in order to raise the price so that it represents their expectations.

After closing the market on the 12th of June 2009, it was expected that the stock prices represent the aggregated valuation of all participants. While every active participant provided individual information in the market via buying/selling orders, the mechanism aggregated them. Once the market was closed, the innovations were ordered by their market price and then the ranking can be interpreted. The results are shown in Section 5.3. As a benchmark, opinions from decision makers and an identical, parallel market for experts were evaluated. From decision makers, a ranking was collected without them having traded in the market to compare it to the market results. Unfortunately, the experts traded very little that the results were not usable for further interpretation. The comparison is described later in Section 5.3.

5.1.2 User Interface

For the experiment, a user interface was designed in order to provide a convenient way to access all market functionalities whereas the market functionalities were similar to those described in Section 4.1.1. Once a trader logged in to the market system, the start screen with a short introduction is shown. On the left hand side, a navigation bar provides easy access to the trading screen, the despot view as well as the ranking screen, where all traders are listed, sorted based on their depot value. A selection of screenshots of the user interface are described in Appendix B, Figures B.13 - B.19.

[3]The automated market maker's strategy was to choose a random number out of the interval [30;70] in steps of five shares.

5.2 Design Objectives

The design objectives of Information Markets are manifold. The first objective is a high motivation of participants. It can be assumed, that the more participants are motivated, the trading activity of Information Markets increases. The same holds for the acceptance of Information Markets by participants. If a method is not accepted by participants, it will not produce accurate results. Therefore, the field experiment was conducted in order to provide an indication for the fulfillment of the design objectives.

Three major objectives motivated the conduction of the field experiment. The first objective was to investigate the motivation of participants in using the market system via their trading activity and a paper-based survey during the workshop. The motivation of people in using an Information Market is a very important step towards the successful application of it. Besides, harnessing implicit knowledge from participants is also important. The aggregation of information in markets can only work properly, if implicit information can be extracted from traders. The second objective was to investigate employees' acceptance of Information Markets. For the successful application of Information Markets it is necessary that employees accept a method, otherwise they may not use it. In the third design objective, the results of an expert panel and the Information Market were supposed not to differ. Therefore, several design objectives focusing on the aspects mentioned above were developed, which are described in the following and investigated in Section 5.3:

1. Traders use the Enterprise Information Markets
   a) Trading activity is equally spread over time
   b) Traders are active during the whole market duration
   c) Employees are motivated to use the Information Market
2. Information Markets are accepted by employees
   a) Employees assess the method of using Information Markets in an enterprise context positively
   b) The Information Market is accepted by employees
   c) Employees perceive that the EnBW is able to better assess innovation
3. Results of the Information Market and an expert panel do not differ in innovation contexts

Design objective 1 and the relevant subordinated objectives are intended to indicate how traders are motivated to actively participate during the market period. In innovation contexts, innovation cycles may last several months or even years (Docter et al. 1989). Thus, it is important to keep traders motivated. In innovation contexts, new information about the feasibility of an innovation is likely to occur. For example, a major breakthrough in technology may support an innovation to be realized. In long lasting Innovation Markets, news about changes in technology may be a motive for traders to change their expectations about the innovations in the market and let them change their depot structure and, therefore, market prices. In turn, other traders respond to such activity. The investigation of design objectives 1 a)-c) is introduced in Section 5.3.1.

Design objective 2 is also subdivided into several design objectives. These objectives are intended to get an indication of how employees estimate the value of Information Markets for a company. The investigation about design objective 2c, which states that employees perceive that the EnBW is able to better assess innovations, provides valuable evidence of trust and acceptance for EIM by employees as well. This is a major prerequisite for the employment of EIM in companies. The results are described in Section 5.3.2.

Design objective 3 refers to the results of the Information Market and investigates if the Information Market's results are similar to the results of an expert panel. The Information Market as well as the expert panel provides a ranking of innovations and can therefore be compared. The results of the Information Markets are expected to be similar to the result of the expert panel in the best case. The results will be discussed in Section 5.3.3.

5.3 Experiment Results

This chapter is divided in two subsections. The first Section 5.3.1 addresses the investigation of the activity, the activity level as well as the motivation of employees during the field experiment according to design objective 1. Descriptive results like trading activity as well as survey results are introduced to provide evidence for the motivation of traders. Second Section 5.3.2 investigates the acceptance of EIM by employees which is derived from the trading activity and results from a survey according to design objective 2. In Section 5.3.3, the results from decision makers are analyzed compared to the result of the Information Market whereas Section 5.3.4 provides the development of a confidence score in order to further discuss the results of Section 5.3.3 according to design objective 3.

5.3.1 Motivating Employees

One of the challenges of innovation management is the involvement as well as the motivation of employees (cp. Figure 5.2). In the next section, the market activity of the EnBW Information Market is analyzed regarding the overall activity of participants. As mentioned in Section 3.1.2, the self-selection process in markets encourages interested and motivated participants who think they can make a profit by providing their information.

5.3.1.1 Market Activity

Figure 5.3 shows the stock price changes for each stock over time. The stock prices for several products vary heavily, which is an indication that trading activity must have been high during the market period and information was processed.

In order to further analyze the trading activity, Figure 5.4 shows the trading activity on a daily average basis of all transactions where human traders were involved. Similar to the experiment described in Chapter 4, an automated market maker mechanism was actively trading in the market. It's presence showed that it

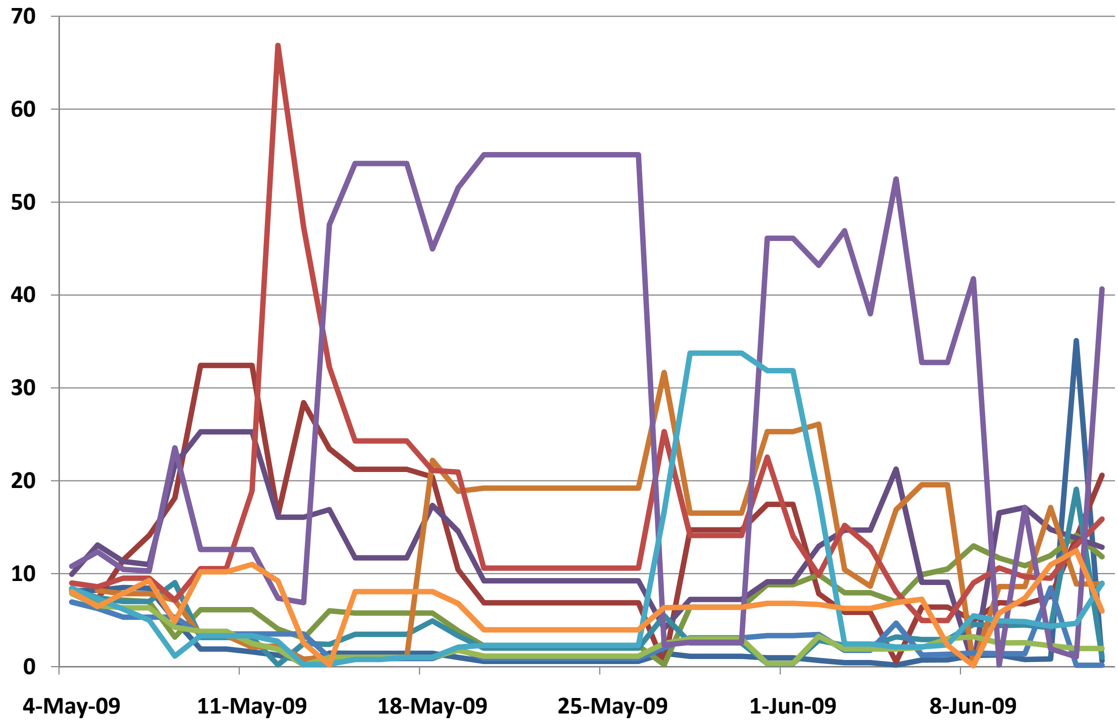


Figure 5.3: Stock Prices Overview

is capable of increase trading activity, market liquidity and, thus, market efficiency whereby it only reacts once a human trader did a transaction. The following figures focus on those transactions at least one human trader was involved.

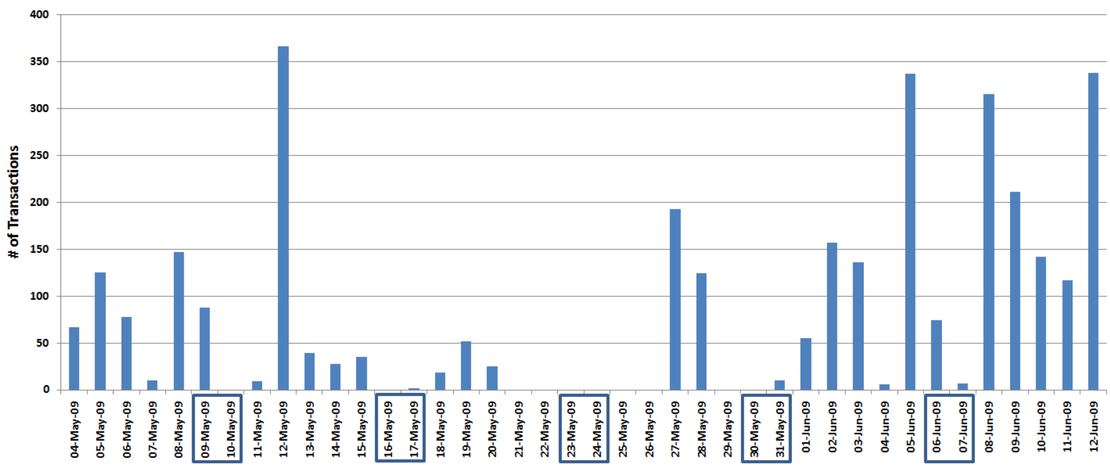


Figure 5.4: Trading Activity

One can see that between the 21st and 26th of June no transaction occurred. During this period, there was a nationwide holiday on the 21st of June and many employees took one day off on the 22nd of June. Besides this, an overall trading activity was observable almost every day. In total, trading activity occurred on 30 out of 40 trading days, even on weekends. In Figure 5.4, the weekends are marked with blue boxes. The daily trading average was 110 transactions with human involvement with a minimum of two and a maximum number of 366 transactions.

In total, participants caused more than 2.000 transactions and submitted more than 4.000 orders.

Figure 5.5 shows the number of transactions per trader in an descending order. In total, the most active trader did slightly more than 1.000 transactions and the least active trader did only one transaction.

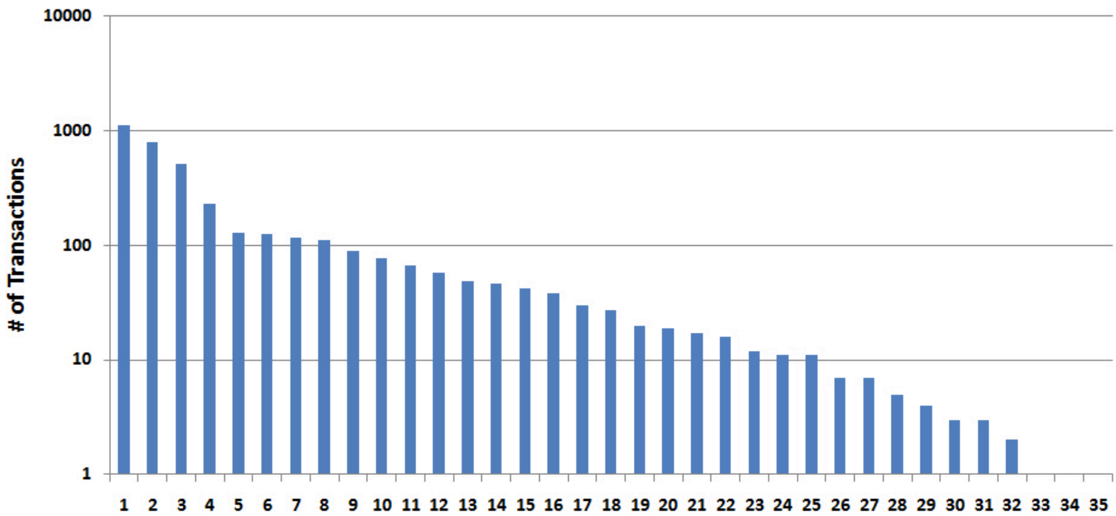


Figure 5.5: Transactions per Trader

The results in figures 5.4 and 5.5 indicate that design objectives 1 a), 1 b) and 1 c) are met. Concerning 1 a), the trading activity is spread over the whole market period. The trading activity decreased at weekends and only a few days were observable with no trading activity. That is in line with what one might expect. The worst expectation, that the trading activity would only be observable at the beginning of the market period, can be denied.

Design objective 1 b) is also achieved. In total, 110 workshop participants were invited to join the market after the innovation workshop. About one third followed the invitation and traded in the market. Approximately ten traders triggered at minimum 100 transactions. About ten traders caused between 100 and ten trades whereas further ten traders did less than ten transactions. That is also what one can expect and is a typical distribution of trading behavior according to other Information Markets (cp. Section 4.4.1).

Table 5.2 shows the final prices of the innovation market. As described in Section 5.1.1, the Information Market will be compared to an expert market as well as results from a questionnaire for decision makers. Unfortunately, the expert market only generated seven transactions, which are too few to serve as a benchmark. The experts were mainly employees from companies/agencies affiliated to EnBW and held the presentations at the first day of the innovation workshop. Therefore, they did not have a major interest in evaluating innovations for a company they are not working for. Ex ante, this result was not expected. It was planned to combine the payout function of the Information Market with those of the expert market. This was also announced on the start screen of the Information Market (cp. Figure B.13). The prices in the expert market did not change that much that after the final payout the ranking of the Information Market was influenced after the combination. The payout function of the Information Market for employees was weighted one third to the expert market weighted with two thirds. The intention of this weighting was to avoid that participants of the Information Market get the impression, that their result at the end of the market period would be taken as a final decision and the top rated innovation would be implemented. With a weighting of one third, participants of the Information Market had the only incentive to imagine what the expert market's result would be. It was ensured, that no participant was able to see the intermediate result of the other market. Therefore, the maximum expected payout of one participant could only be realized revealing the true valuation about the innovations. The weighting of 1/3 and 2/3 was chosen because if the proportion have been 1/2 and 1/2, participants in the Information Market could get the impression that they have as much weight as experts once the results would be combined. In the worst case, participants could have had the incentive to distort prices and affect the results of the expert market. Therefore, the weight of the Information Market had to be slightly lower than the expert market's weight that employees had no incentive to trade strategically. Hence, the decision was to weight the Information Market with one third and the expert market with two thirds.

As one can easily see, the results of the expert market did not change the overall ranking of the total payout prices after the combination. Therefore, the payout was done with the weighting, although the expert market was illiquid.

Table 5.2: Combined Prices from the Expert Market and Information Market: The combined price for each contract consists of the combination of prices from the Information Market and the results of the Expert Market. The Expert Market was weighted 2/3 whereas the Information Market was weighted 1/3.

Name	Combined Price	Expert Market	Information Market
All in One	17,13	7,50	36,40
MEREGIO Platform	12,58	7,90	21,94
Web 2.0 Poster	11,64	8,34	18,24
xing@enbw.com	10,92	8,34	16,07
Parallel Document Processing	9,25	8,34	11,08
Hardware Inventory	7,56	8,34	6,00
Mobile Metering	7,54	8,34	5,93
Home Automation	6,32	8,34	2,28
New Contact Networking	6,10	8,34	1,62
Intelligent Calendar Management	5,85	8,34	0,86
Digitizing Business Cards	5,83	8,34	0,81
Twitterinfo	5,72	8,34	0,49

Table 5.3 shows statistics for the whole market duration of the trading days. In the columns, the min, max, median (med) and diameter ($\varnothing$) are shown for transactions with at least one human trader on the buy or sell side.

The values in the columns per share have different min and max values, which indicates that prices differed and information was processed. The diameter shows the average for each stock. Detailed results of Table 5.3 per week are illustrated in Appendix B, Tables B.1 and B.2.

Table 5.3: Market Statistics: Minimum, maximum, median and average trading prices are calculated for each stock.

ID	*min*	*max*	*med*	⌀	Name
1	0.74	8.40	8.34	3.84	Twitterinfo
2	0.10	50.0	6.60	16.47	MEREGIO Platform
3	0.10	14.45	8.80	7.32	Home Automation
4	0.10	40.0	13.79	18.14	Parallel Document Processing
5	0.50	20.0	20.0	4.19	Intelligent Calendar Management
6	2.01	40.0	8.34	16.74	Web 2.0 Poster
7	1.00	8.71	7.05	4.66	Digitizing Business Cards
8	4.13	100.0	9.50	21.93	xing@EnBW.com
9	0.50	8.34	8.34	4.48	New Contact Networking
10	0.10	77.0	9.00	25.72	All in one
11	0.30	48.5	9.00	6.71	Hardware Inventory
12	0.10	12.0	6.21	5.78	Mobile Metering

In Information Markets, one may expect that traders trade intensively in the early days of the market. They have an initial expectation about the innovations alternatives and therefore they set up their depots according to these expectations. They may favor one or two innovations and trade them at higher prices compared to the innovations which will not be that beneficial for their company. After they set up their depots according to their initial expectation, it can be assumed that most traders are satisfied with their depot and wait until stocks will be paid out. In case that the market is open for six weeks, one should observe the most trading activity in the first one or two weeks. Typically, information is needed to prompt traders to update their expectations. But if a company does not provide or support information about future innovations and make it available to their employees, they will not update their expectations. In the field experiment, new information was available to traders via an internal wiki where all tradable innovations were described and traders had the chance to discuss them with each other and build new information in a forum. Other employees could see these discussions and sentiments of traders and use it to update their own expectation about the success or failure of the innovation alternatives. Therefore, it is beneficial, if a continuous high number of transactions can be observed in the market for two reasons: Firstly, traders have to update their portfolios constantly because transaction prices change often. Thus, their depot value changes based on the transaction prices and may prompt them to update it. Secondly, traders are encouraged to inform themselves about the innovations because only if they gain knowledge about what they trade they are able to bring the price in the direction they think the innovation should be based on their assessment.

In Table 5.4, the number of trades of the ten most active traders at each trading day is illustrated. It is remarkable that 1182 of 2145 orders occurred in the last ten trading days. During the whole market duration of 40 days, only 10 days were without any trading activity. On the 05th of June 2009, the most active day was observed with 328 orders. 264 of them caused from only one trader. In total, it is impressive that the trading activity was constantly high and did not decrease over the market duration.

Table 5.4: Top 10 active Traders: The trading activity (number of trades) of the top ten traders (most active) was analyzed for each trading day.

	Traders										
Date	1	2	3	4	5	6	7	8	9	10	Sum
04 May 2009		5	13		47				5	1	71
05 May 2009	3		2		34	92			4	4	139
06 May 2009			3	38						4	45
07 May 2009			4						2	5	11
08 May 2009	18	8	19	6	26	3					80
09 May 2009	19	27									46
10 May 2009											
11 May 2009		3							1		4
12 May 2009			11		19				2		32
13 May 2009	2		8					2	2	10	24
14 May 2009	2	3	6						2	4	17
15 May 2009			1								1
16 May 2009											
17 May 2009	2										2
18 May 2009				2	2				3		7
19 May 2009									1		1
20 May 2009	7										7
21 May 2009											
22 May 2009											
23 May 2009											
24 May 2009											
25 May 2009											
26 May 2009											
27 May 2009	82	15							1	32	130
28 May 2009	68		14							14	96
29 May 2009											
30 May 2009											
31 May 2009											
01 June 2009	32										32
02 June 2009	40	12	21	1							74
03 June 2009		123	1						3	17	144
04 June 2009		2									2
05 June 2009	264		13				18	33			328
06 June 2009	37	27					7				71
07 June 2009	2										2
08 June 2009	73		25	43			15	1	3		160
09 June 2009	23	41	1				17	5			87
10 June 2009	3	27	30	3			3		6		72
11 June 2009	8	79	10								97
12 June 2009	153	73	5	29							260
13 June 2009	4	13	13	73							103
Sum	842	458	200	195	128	95	60	41	35	91	2145

In Table 5.5, the number of "correct" transactions is shown. This analysis was conducted ex post, after the final price was determined. Hence, orders of each trader are analyzed, if the direction of a trade moved the price towards the final value. For example, a buy order is tagged as "correct", if the limit price of that order was lower than the final value and the order was executed. Otherwise, if the limit price of a sell order is lower than the final value, the order is tagged as "incorrect". 164 out of 280 total observations indicate that the market processed positive trading directions. If

Table 5.5: Trade Direction: The success per trader can be measured with an indicator about the "correctness" of trades. Ex post, it can be analyzed how often a trader did a buy/sell trade depending on the current stock price. A buy/sell trade was correct in case of under/overvaluation compared to the final value. The relation of correct trades to the total number of trades leads to the trade direction coefficient per trader and per stock.

Trader	Stocks											
ID	1	2	3	4	5	6	7	8	9	10	11	12
2	0.03	0.42	0.45	0.66	0.10	0.44	0.07	0.07	0.07	0.69	0.23	0.23
3		1.00										
8	0.10	0.34	0.58	0.50	0.10	0.50	0.33	0.33	0.33	0.37	0.10	0.33
13		0.00										
15	0.83	0.22	0.29	0.84	0.56	0.00	0.83	0.83	0.83	0.10	0.21	0.42
19	1.00	0.00	1.00	1.00	1.00	0.00	1.00	1.00	1.00	0.00	0.22	0.00
21		0.20		1.00		1.00		0.00		1.00		
25	0.20	0.50	0.67	0.50	0.33	0.00		0.00		0.50	0.20	0.50
27	0.00	0.00	0.00	1.00	0.00	0.00	0.50	0.50	0.50	0.00	0.00	1.00
32	1.00	0.52	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.13	0.67
38	0.00	1.00										1.00
41	0.20	1.00	1.00	0.80	1.00		0.00	0.00	0.00	0.60	0.00	1.00
42				1.00								
54		0.00				0.00		0.00		1.00		
55	0.00							0.00		1.00		
65	0.00	1.00	0.25	1.00	0.63	0.00		0.00		1.00	0.09	1.00
66	0.00	1.00								0.00	0.00	0.00
69						1.00		0.00				
72	1.00		1.00					0.00			1.00	0.50
79	1.00	1.00		1.00		0.00	0.00	0.00	0.00	0.00	0.00	1.00
81							1.00		1.00		1.00	1.00
85	0.00		0.40	0.50			0.00	0.00	0.00	1.00	0.00	
98	0.17	0.67	1.00	0.67		1.00	1.00	1.00	1.00	0.78	0.00	
100	0.00	1.00		1.00	0.00	0.00		0.00		1.00	1.00	
102	0.55	0.15	0.89	0.74	0.33	0.77	0.53	0.53	0.53	0.62	0.07	0.56
103	0.00	0.14	0.89	1.00	0.00	0.67	0.00	0.00	0.00	0.60	0.50	0.33
106	0.00	0.00						0.00		1.00		0.00
109	0.00		1.00	0.50	0.00	1.00	0.00	0.00	0.00			0.00
121	0.50		1.00	1.00			1.00	1.00	1.00	0.00		
128	0.00		0.00	0.00			0.00	0.00	0.00	0.00	0.00	1.00
129	0.84	0.21	0.53	0.77	0.34	0.37	0.62	0.62	0.62	0.20	0.38	0.03
141	1.00	0.00	1.00									
143	0.43	0.50	1.00	0.86	0.00	0.50	0.07	0.07	0.07	0.63	1.00	0.35
149	0.00	1.00		1.00	0.00	0.00	1.00		1.00	0.00		1.00
154	1.00			0.00								
155			0.00					0.00		1.00		
203	0.01	0.03	0.05	0.10	0.02	0.04	0.04	0.04	0.04	0.06	0.06	0.02

a cell is not allocated, the trader did no transactions in that stock. If the cell is tagged "0.00", the trader did transactions in that stock, but all transactions moved the price away from the final value.

Altogether, the analysis of the trade direction indicates which traders provided a positive contribution to the market result. Traders with top performances can be consulted for further interviews about their estimations or to take part in ongoing innovation activities since they showed an accurate understanding about the tradable contracts.

5.3.1.2 Survey Results for Motivational Aspects

During the workshop, participants were asked about their job profile in order to learn about their background with a survey[4]. The result is illustrated in Figure 5.6[5]. Most participants were regular employees without executive or innovation tasks. The second group can be tagged as employees with at least 50 % innovation tasks and personnel responsibility. Only ten employees had executive functions whereas six people were something else like external employees or working students. Altogether, workshop participants were invited from all nine EnBW sub-divisions.

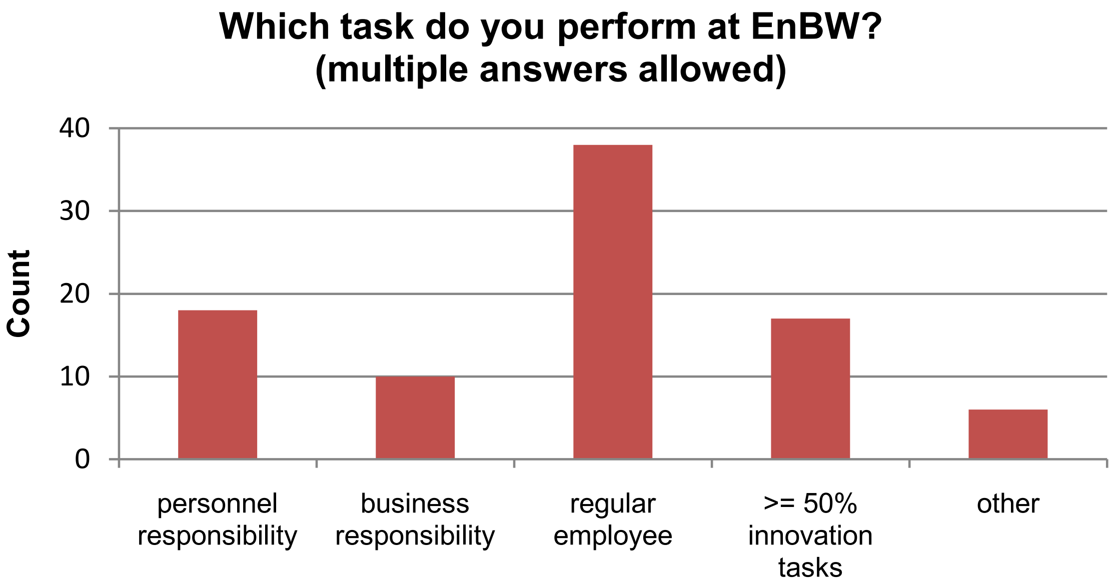


Figure 5.6: EIM Survey: Participants

In the following, the trading activity of the ten most active traders is analyzed in order to identify which kind of employees were most active. A common analysis in Information Markets is the identification of lead users. Lead users are important traders who are most active and react very quickly in order to adjust their information in the market. Furthermore, they are highly interested in improving, e.g., new products, and face the need for future products or try to find solutions for their needs months or even years before (von Hippel 1986; Urban and Von Hippel 1988;

[4]The survey was conducted in German language and is translated in English language in this work. For the investigation in this chapter, several questions are highlighted. The original questionnaire in full length is illustrated in Appendix B, Figures B.20 - B.25. In total, 100 questionnaires were handed out whereas 69 questionnaires returned. Question 1 was about the affiliation participants, e.g., if they are executives, regular employees or a regular employees with innovation tasks or other responsibilities. Questions 2-7 were about the approach of using Information Markets for innovation assessment whereas questions 8-16 were about the business culture concerning innovation within the company. Questions 2-7 were further intended to learn about the motivation of employees in participating Information Markets and their expectation about how the approach is suited to assess innovations in companies.

[5]This question refers to question 1 in Figure B.20.

von Hippel 1988). That makes them a potential source for innovative ideas. The participation in Information Markets shows that they have a higher involvement in contracts than other traders. According to von Hippel (1978) and von Hippel (1986), companies should integrate lead users in their development processes, once they identified them. Table 5.5 shows the ratio of each active trader in every product. One may easily see that some traders traded every product and have mainly a positive score in each product. This means that they bought undervalued share and sold overvalued shares correctly. One cannot expect the score to be 1, because then every trade would have been in the "right" direction. Some traders did hundreds of trades and, therefore, it is unlikely that every trade was right. The analysis in Table 5.4 and Table 5.5 allows the identification of traders which played an important role in the price discovery process. Traders were analyzed concerning their domain of work, e.g., if they are a regular employee, or an executive etc. in order to see, if the market was dominated by a certain type of employees or if traders are representative for the company. The following list reveals the domain of work for the top ten most active traders:

1. business responsibility
2. regular employee
3. regular employee
4. personnel responsibility
5. other (external)
6. regular employee
7. regular employee
8. personnel responsibility
9. regular employee
10. regular employee

Altogether, this is a result very similar to the result presented in Figure 5.6. The group of people mainly responsible for market prices consist of an appropriate representation of employees. As mentioned in Section 5.3, one can conclude that the market did not motivate only the regular employees in participating the market but also executive employees with personnel and business responsibility. The higher management is appropriately represented by three very active participants. Hence, this result indicates that the higher management showed their commitment since they traded actively. Furthermore, even the motivation of regular employees, which is another challenge in innovation management, can be confirmed, because their trading activity within the top ten traders is also observable.

Another challenge mentioned in Figure 5.2 is the lack of transparency due to missing or wrong information. One can argue that the existence of the Information Market is a source of information itself. Participants can see which innovations are actually traded in the market and, thus, may be implemented. In addition, a wiki system was provided to host textual descriptions where participants could review the innovations and share their expectations in a discussion forum as well.

On the one side, information is essential for traders to interpret it and to provide it to the market. On the other side, they provide their estimations via an user interface in a virtual market system which denotes an effort for traders. In the following, the individual perceived effort was questioned in the survey. Figure 5.7[6] shows the results for the question about the effort of participants in using EIM. Participants answered with an average of 3.54 and a median of 4.00, where 5 denotes "very high" and 1 denotes "very low". The variance of 0.72 (standard error 0.85) indicates that the participants assess the effort of using EIM is relatively high. This is reasonable, because using an EIM is definitely more complex than filling out a questionnaire. In an EIM, participants have to monitor stock price changes frequently. In a survey, participants have to fill out a questionnaire whereby this represents only a snapshot – but associated with less effort, based on the length of the questionnaire.

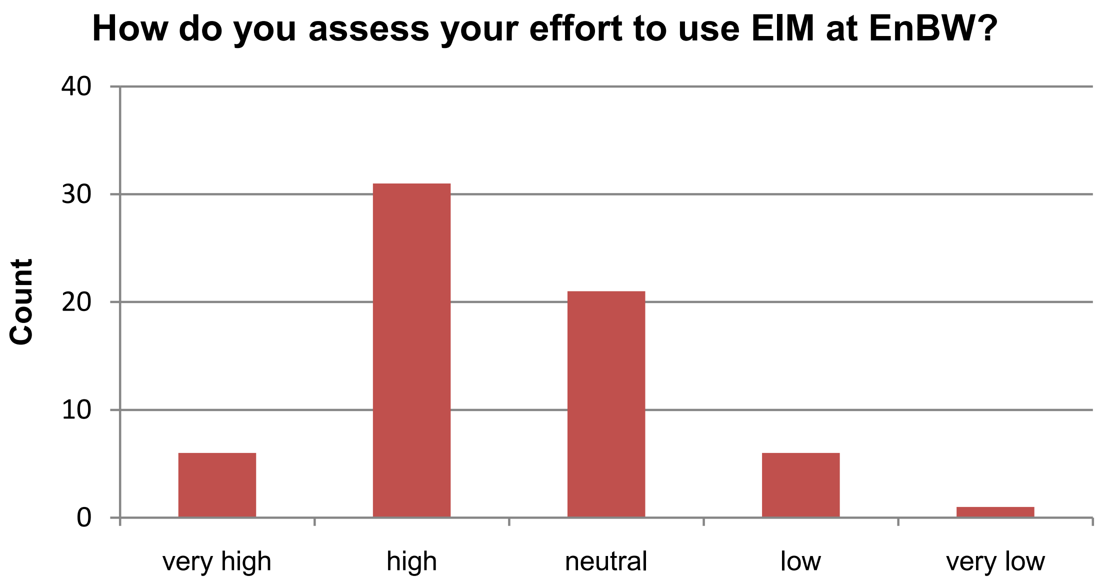


Figure 5.7: EIM Survey: Effort

Interestingly, the motivation of using an EIM for a longer time is well-balanced. The results are shown in Figure 5.8[7]. The average was 2.85 and the median was 3.00, where 5 denotes "very high" and 1 denotes "very low". In that case, the median as well as the average indicates that the motivation is perceived as neutral. This is also comprehensible, because if a method is perceived as more intensive in their usage, the motivation should be lower compared to a questionnaire. On the other side, in an EIM a performance-based payout mechanism can foster the motivation in using an EIM, which is not applicable in questionnaires.

Regarding design objective 1 c), the motivation of employees is limited. The average on the 5 point Likert scale where 5 denotes – very high – and 1 denotes – very low – is at 2.85, slightly below the middle (3). The median was 3.00, the variance was 0.92 which indicates that the overall motivation for the participation in EIM is moderate. A correlation analysis shows that the effort and the motivation

[6]This question refers to question 4 in Figure B.21.
[7]This question refers to question 5 in Figure B.21.

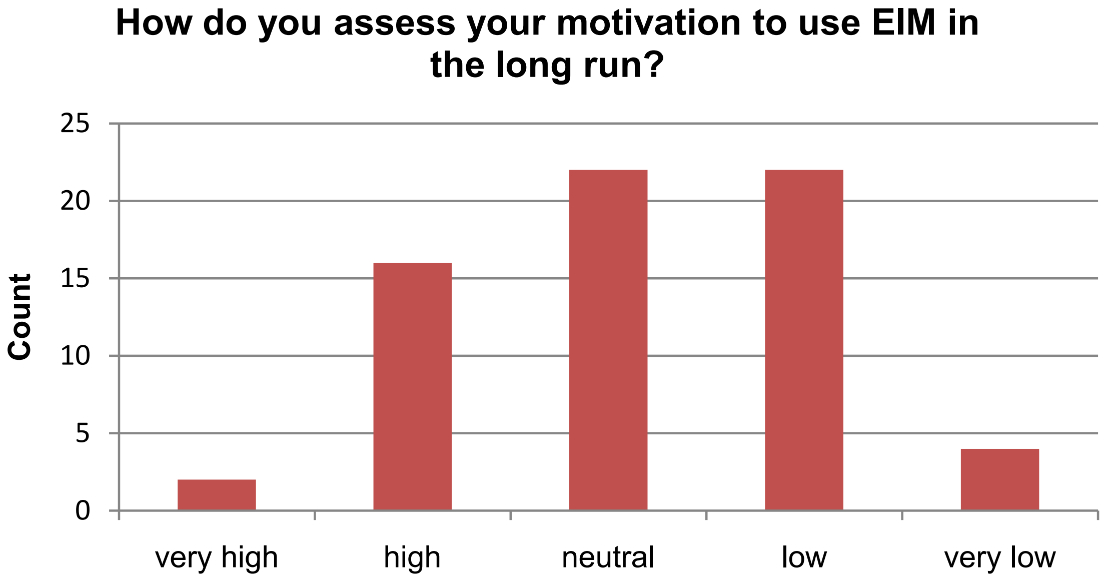


Figure 5.8: EIM Survey: Motivation

is low correlated[8] with a negative correlation coefficient of -0.322. This is reasonable since the usage of a tool takes more effort, it should not increase traders' motivation. Thus, the development of the system should focus on usability in order to decrease traders' effort and in turn, increase the motivation of users.

The analysis of results supporting design objective 1 c) shows that it is partly achieved. This indicates that the incentives have to be further developed in order to foster the motivation of employees. Nevertheless, some employees were extremely motivated as can be derived from the results presented in Figures 5.4 and 5.5. Some traders were very active and caused several hundreds of transactions which indicates a non negligible level of motivation.

In another question, employees were asked which problems they perceive for the usability of EIM. The results are shown in Figure 5.9[9]. The main answer was that people think they have no time to use the information market tool. Interestingly, the second answer was that they think they cannot estimate the value of stocks correctly. That answer opens two directions of interpretation. The first one is that they are not able to transform their expectations into stock prices. The second one is that they are not able to assess the benefits of innovation alternatives for the company correctly.

5.3.2 Acceptance of Information Markets by Employees

A very common way to measure the accuracy of Information Markets is to compare their results to an observable benchmark. In case of sport or political events, the Information Markets' results can be compared to the final values of the sport event outcome or the final values of an election (Berg and Rietz 2006; Graefe et al.

[8] According to Weise (1975), (-0.322) is medium correlated. Other values: (0-0.2] – weak correlation, (0.2-0.5] – low correlation, (0.5-0.7] – medium correlation, (0.7-0.9] – high correlation.
[9] This question refers to question 7 in Figure B.21.

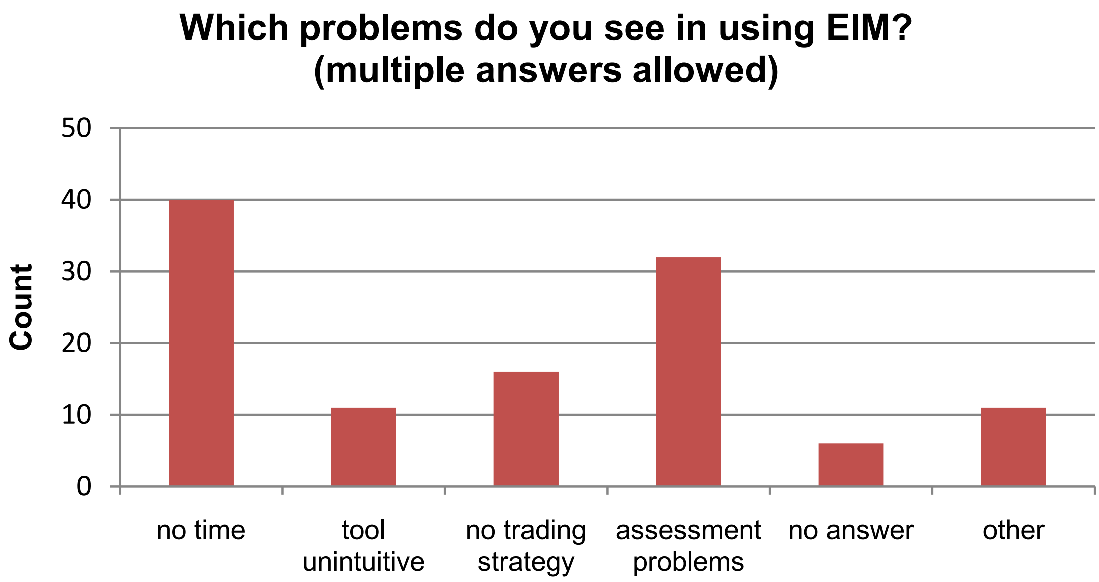


Figure 5.9: EIM Survey: Problems

2009). In case of Enterprise Information Markets (EIM), a similar final value may exist, if sales figures or project run times are to be predicted. As mentioned in Section 2, EIM are applicable even if no final value is observable (Soukhoroukova and Spann 2005; Chen et al. 2010). In case that no observable real world benchmark or event can be used to determine the accuracy of an EIM, other benchmarks need to be used. One option introduced by Spann (2002) is to run two markets in parallel. Traders are only allowed to participate in one market. Once both markets are closed, the final values of stocks of the first market can be taken as payout function for the second market and vice versa. Other approaches are reported by Slamka (2009) or Chen et al. (2010) by using the final stock price as payout function. It is doubtful to use the last transaction price as benchmark because the payout function has to be transparent to traders in EIM and therefore strategic behavior may be supported. Traders may tend to trade their favored stocks as they want the market result to be and that should not be possible. The payout function should lead traders to reveal their real expectation based on the objective the market should fulfill. The payout function must be the dominant guideline that strategic behavior is neither rewarded nor incentivized.

For the field experiment introduced in Section 5.1, two benchmarks were intended to be compared to the results of the Information Market employees had used. The first one was an identical market running in parallel. Dedicated experts chosen from EnbW and also presenters of the presentation slots mentioned in Section 5.1 were supposed as participants for the expert market. These experts were employees mostly from external companies affiliated with EnBW. In total, eight experts were supposed to be in the expert market. Unfortunately, only seven transactions were observed and, thus, the result cannot be consulted to serve as a benchmark. The reason might have been that the experts were not originally employees of the EnBW and therefore had no interest or information to trade in the expert market. Therefore, the result of the expert market was discarded.

The second benchmark was the comparison to decision makers at EnBW. In the past, the innovation workshop was conducted twice and every time the decision makers came to their decision which innovation should be implemented by themselves. In 2009, the Information Market was an additional method to get further information from employees which was a rather new situation. In the next section, the results of both the Information Market and decision makers will be illustrated.

5.3.2.1 Expert Expectations and Information Markets

A common benchmark is the usage of expert opinions to measure the accuracy of Information Markets. In scientific literature, it is reported that Information Markets consequently outperform experts in various fields of application (Spann and Skiera 2004; Soukhoroukova 2007; Graefe 2008a; Graefe 2008c). But it is only sensible to compare expert opinions to the market result if it is assured, that the experts are the best available benchmark for the given problem. In an innovation context, even experts may not have superior information which innovation is most profitable. In this work, a combination of several information sources is considered most promising for a company trying to identify the most profitable innovation by involving their employees in decision processes. As mentioned in Section 3.1.2, traders participate in markets only if they have superior information. Otherwise, they will not be able to realize positive outcomes in the market. Thus, the market may be open for a sensible partition of relevant employees and only those will participate who think they can bring information in the market and make profit. A common challenge in selecting experts for expert opinions is to find them. A research direction in Information Science focuses on that problem (Campbell et al. 2003; Yimam-Seid and Kobsa 2003; Hawking 2004; Balog et al. 2006). But somehow companies manage to form an expert group – as they have to do in order to get a decision which innovation they should realize. Either way, the expert group or a project team will be formed. The field experiment competes with the expert group as a parallel method to rank innovations mentioned in Table 5.1. The company has two major benefits of having a market parallel to the expert opinion:

1. Additional ranking of innovations
2. Information from another group of employees

Alltogether, there are four imaginable outcomes of the two benchmarks which are described in Table 5.6.

Table 5.6: Possible Outcomes

		Market	
		positive	negative
Experts	positive	good (1)	action required (2)
	negative	action required (3)	good (4)

In the best case (1), the market as well as the experts come to the same or similar ranking which is aligned with the expectation of decision makers. This indicates that the majority of people involved in innovation processes think the same way about the most promising innovation. In the second (2) and the third (3) case, either the experts or the market point in different directions. For the company, this is an indication that at least one group assess the innovations differently. In innovation contexts, one cannot evaluate that the one innovation is beneficial and the other is not. Therefore, the indication in case (1) is mostly desirable, because the decision makers in the company may have a suggestion, which innovation they should support by themselves. Once both, market participants and the experts, assess the same innovation as beneficial, the decision to make is easier to justify by decision makers.

In case (2) and (3), it is of high importance that before the final decision is made the decision makers check the innovation again, eventually through another control group like external consultants or internal counselors. The different direction of the market and the experts' opinions alerts decision makers to reconsider if they should go for an innovation or not. In the worst case (4), the market as well as the experts point to the same direction, but both groups may have a different perception about the innovations compared to decision makers. If decision makers have no such markets, they must decide which innovation they should go for. Either way, the combination of experts and Information Markets is a way to have the possibility to get various opinions from groups with different perceptions. Via the self-selection process, only employees with relevant knowledge are expected to join the market. Traders working in the sales division may possess information about the needs of customers or business partners they know and makes their decisions about an innovation based on that information. Other employees maybe have different business networks and therefore, they can provide that information to the market – even about the same innovation (Plott and Sunder 1988). Moreover, for the company it does not have to be of any disadvantage having an additional information source which innovation employees favorize. In contrast, they have an additional control group to the experts or consultants they always have in order to identify the most beneficial innovation.

In case that the market and the experts have the same expectation about the innovations, it may happen that the decision makers have a different one. That is meant by (negative/negative). But it cannot be determined ex ante, in which sector in Table 5.6 the results of the three entities (decision makers, experts, innovation market) are, because sector (1) and (4), as well as (2) and (3) are possible, depending if the results from decision makers can be assumed as right or false, which is not possible ex ante. Even ex post, it is not feasible to check if the results of a "wrong" result turn out to be right, because not all innovations can be implemented. Even if the best innovation is lower ranked as others, it may never be noticed. But this cannot be proved until all innovations are implemented and evaluated against each other. As already said, it does not have to be of any disadvantage having additional information about the expectation of employees via markets and experts on the other side. It may help to avoid implementing a barely advantageous innovation.

5.3.2.2 Survey Results for the Acceptance of Information Markets

After the first day of the innovation workshop, a survey with several questions was conducted in order to get valuable information from the participants about innovation management via Information Markets. The survey was paper-based and was handed out after the slot about innovation management with Information Markets. In Appendix B, the complete survey is illustrated. The objective of the survey, which was conducted before the field experiment started, was to learn about the employees' perception about the Innovation Market approach.

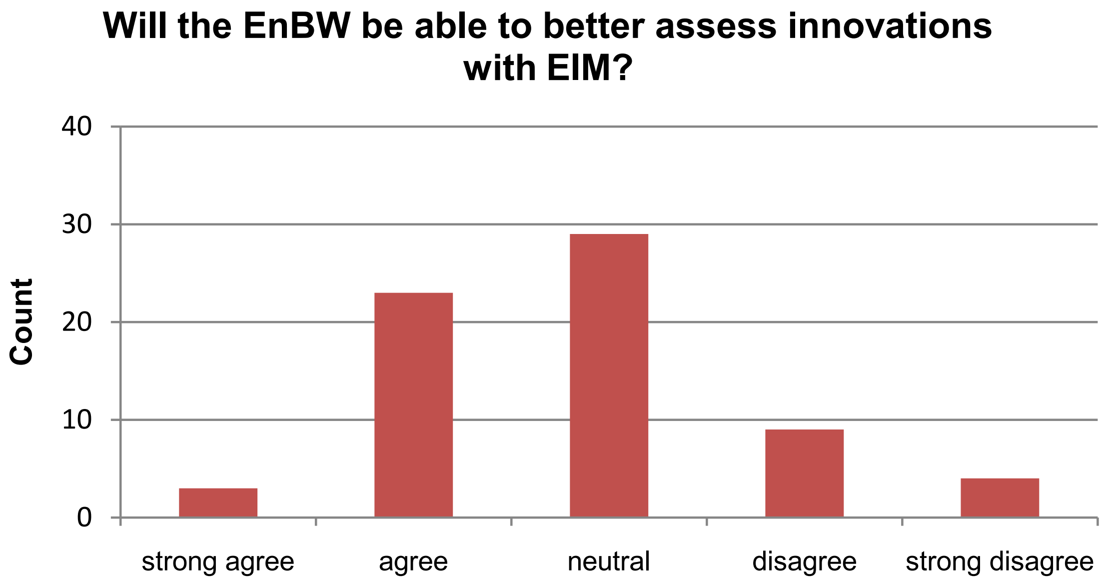


Figure 5.10: EIM Survey: Innovation Assessment for EnBW

Figure 5.10[10] shows the results of the question: "Will the EnBW be able to better assess innovations with the EIM?" In total, 65 participants answered that question. The 5 point Likert scaled question, where 5 denotes "strong agree" and 1 denotes "strong disagree", was answered with an average of 3.19 and a median of 3.00. The variance was 0.86 and the standard deviation was 0.93. One can see that the overall opinion of employees with an average of 3.19 is positive, that most of them believe that the approach of using EIM is beneficial for the company. The variance as well as the standard error and especially the median indicates that the majority of the respondents agree, that the company can assess innovations better with EIM. For employees, it is a simple participative way to make their information available to executives. One challenge in companies with strict, top down hierarchies, is that employees may think they do not have impact on decisions and the executives make their decisions independent of the employees' opinions. It is not feasible asking each employee about his opinion, but with EIM, interested employees can join the market and offer their information whereas the market mechanism aggregates each individual information effectively. Moreover, this is also a benefit for decision makers and executives, as already mentioned in Section 2.1.

The interpretation from Figure 5.10[11] continues in Figure 5.11. In this question, the workshop participants were asked, what their opinion is about the approach of using EIM to assess innovations. The results are shown in Figure 5.11.

[10]This question refers to question 6 in Figure B.21.
[11]This question refers to question 3 in Figure B.21.

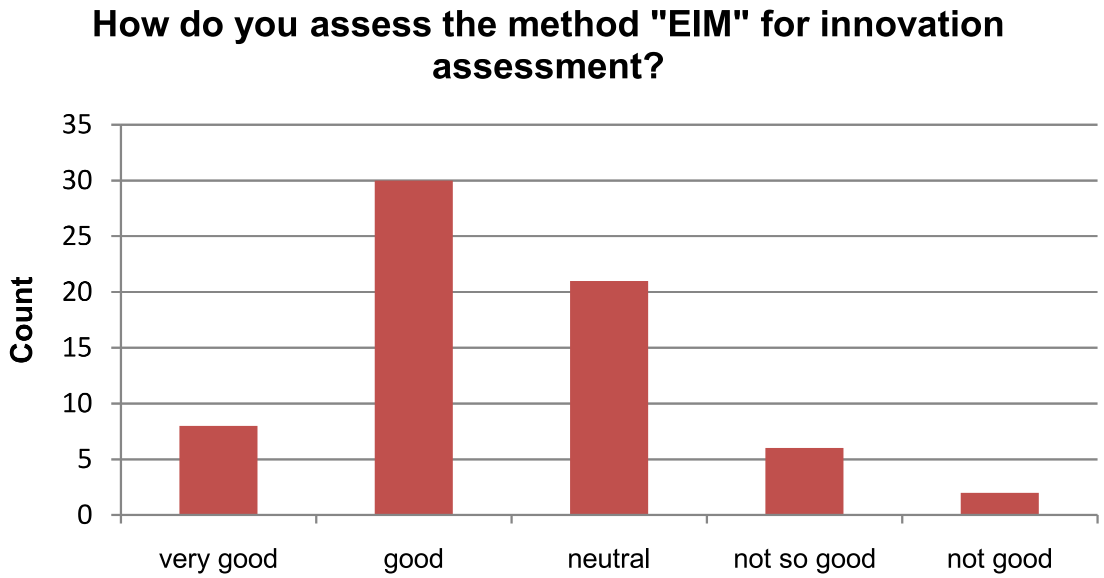


Figure 5.11: EIM Survey: EIM Approach

In total, 67 participants answered the question with an average of 3.54 and a median of 4.00, where 5 denotes "very good" and 1 denotes "not good". The variance is 0.86 and the standard error is 0.93. This indicates that the employees judge the approach of using EIM for innovation assessment as "good". This fosters the results from Figure 5.10. Both results show a medium positive correlation of 0.566[12], which means that the company is considered to assess innovations better with EIM. Furthermore, the correlation is significant at the 5 % level. In general, participants consider EIM as a good method for innovation assessment. In addition, the results from the question shown in Figure 5.10 indicate, that employees are sure that the EnBW is able to better assess innovations with EIM (cp. design objectives 2 a), 2 c)). The combination of the results presented in Figures 5.11, 5.4 and 5.5 indicates that the EIM is accepted by employees and is therefore actively used. This indicates that design objective 2 b) is met and is therefore a valuable indication for the employment of EIM in organizations.

5.3.3 Decision Makers vs. Information Market

In order to give an indication about design objective 3, the results of the market are compared to the results of an expert panel. The expert panel consisted of two experts with consultative functions who are responsible for the implementation of the innovations at EnBW. Before the market started, the experts came to their expectation based on their personal anticipation about the benefit of each innovation. After the market, they revealed their expectations and these were compared to market results. Table 5.7 shows the ranked results from experts and the Information Market.

The results in Table 5.2 show that in the Information Market five stocks were rated above the initial price of 8.33 currency units. In the expert panel, the inno-

[12]According to Weise (1975), 0.566 is medium correlated. Other values: (0-0.2] – weak correlation, (0.2-0.5] – low correlation, (0.5-0.7] – medium correlation, (0.7-0.9] – high correlation.

Table 5.7: Decision Makers vs. Enterprise Information Market

Rank	Decision Makers	Information Market	Price
1	Web 2.0 Poster	All in one	36.4
2	xing@enbw.com	MEREGIO Platform	21.9
3	All in one	Web 2.0 Poster	18.2
4	Intelligent Calendar Management	xing@enbw.com	16.1
5	Twitterinfo	Parallel Document Processing	11.1
6	Mobile Metering	Hardware Inventory	6.0
7	Parallel Document Processing	Mobile Metering	5.9
8	MEREGIO Platform	Home Automation	2.3
9	Home Automation	New Contact Networking	1.6
10	Digitizing Business Cards	Intelligent Calendar Management	0.9
11	Hardware Inventory	Digitizing Business Cards	0.8
12	New Contact Networking	Twitterinfo	0.6

vations cannot be ranked via final prices because the ranking was not originated with a market mechanism. The experts were asked to rank the innovations based on their expectation about the profitability and feasibility. The experts' results in the top five innovations overlap three innovations of the Information Market which indicates, that both methods delivered congruent results. In case of innovation alternative ranked 1, 2 and 3 from decision markets and ranked 1, 3 and 4 of the Information Market in Table 5.7, the results can be categorized as case (1) – or case (4) – discussed in Table 5.6. This indicates, that both, market participants and decision makers in the expert panel come to the very similar results which is a strong indication for the implementation of innovations. For the interpretation of the presented results, it is necessary to further investigate the evolution of stock prices in order to interpret the market results. Thus, in the next section, a metric will be developed to discuss the market results.

5.3.4 Confidence in Stock Prices

The results presented in Section 5.3.3 are mainly based on the last observable trade prices and disregarded how the final price has formed. According to Fama (1970), the last transaction price comprises all available information and is, thus, the best estimation of the represented contract. But in reality, traders do not follow the optimal theoretical concept. Information deficits and misinterpretations can affect market prices and, therefore, last transaction prices are not necessarily the best representation of the aggregated assessment of a contract. This applies especially for events in which no defined end can be determined. For example, the stock price in Figure 5.12 shows a peak in the transaction price at the end of the market duration while the market price was stable until 11th of June.

This development can be explained twofold: On the one hand, new information may have been available which was integrated in transaction prices by the traders. On the other hand, traders may have played the market in order to manipulate the outcome or followed other motives which are described in Section 3.1.2. In case of Twitterinfo, the peak on the day before market close was caused by only a single trader who pushed the price from a level of one currency unit up to 80 currency units in the early morning. Later that day, other traders noticed the distortion and adjusted the price back to the level before. If the market had been closed that day

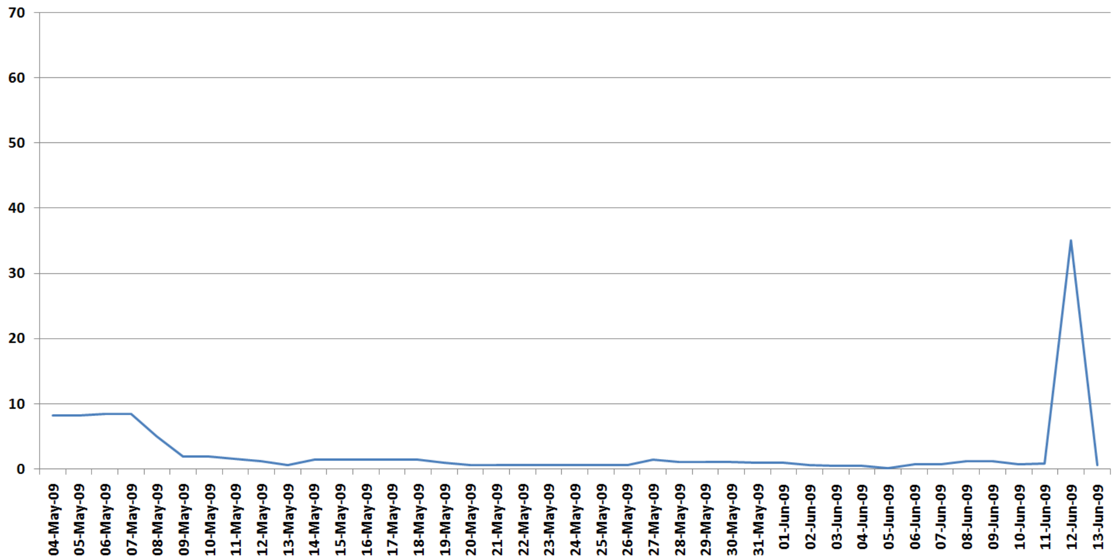


Figure 5.12: Time Serie: Twitterinfo

in the morning, the final price would have been distorted by only one trader, which seems not very "confident" to decision makers. Therefore, the last transaction price does not have to be the best representation of the stock's value. Hence, further information about how the price formed is desirable, especially for events that do not have a defined outcome, e.g., in innovation contexts.

Thus, a confidence score is developed in the following in order to provide further information about how trade prices evolve. Several aspects are considered useful as input for the confidence score such as the number of unique traders, the volatility of stock prices and the number of trades. In the next section, the development of the confidence score is described, before it is evaluated based on the dataset introduced in Chapter 4. It provides an appropriate basis for the evaluation since the final outcomes of the events are known and, therefore, the quality of the confidence score can be evaluated. After the evaluation, the confidence score is applied to the dataset from the EnBW experiment.

5.3.4.1 Confidence Score Development

In order to obtain information about "how" the price of contracts has formed, several market parameters can be considered. For example, the total number of trades indicates if different traders "agree" with the actual price. For instance, if the number of trades in a certain period of time is low, it can be assumed that traders do not think that the price must be adapted to their estimation – or they have other motives as stated in Section 3.1.2. If the number of trades is more frequent, traders perceive the actual price differing to their estimations and start trading. Therefore, besides low overall participation in markets, which can be also a reason for low trading activity, a low number of trades may indicate that traders perceive a consensus given sufficient liquidity.

Another parameter which is interesting to be considered and indicates how many people represent the actual prices is the number of unique traders. Unique traders are single persons involved in the price formation process, no matter how *many* trades they did. From a decision maker's point of view, it is worth knowing how many different traders were involved in the price discovery process. For example, one single trader can cause a price which only represents his estimation. The aggregated estimations of many traders which come to a consensus is a much more valuable piece of information for decision makers in terms of how many people support this price. Thus, the unique number of traders could be considered for the confidence score.

Furthermore, the number of trades per trader is an indicator for the development of the confidence score. This parameter is indirectly linked to the volume which is traded. Traders can, on the one hand, submit one order with a high volume to change the price. On the other hand, they can split up their order with the same volume into several smaller orders with the same effect. The difference is the information they reveal to other traders. If they see one order with a high volume, they may assume that the submitting trader has valuable information and tries to integrate it via only one order. In the other case, submitting several smaller orders to the market does not support such an interpretation (Schwartz et al. 2006). Hence, it cannot be determined why traders choose their number of trades or volume and, thus, these measures are of limited usefulness for the creation of a confidence score.

The volatility of prices indicates the deviation of stock prices from the average. It can be assumed if the volatility, which can be measured by the standard deviation, is low, traders agree to some extent with the actual market price – given sufficient liquidity. If the volatility is high, traders disagree and no consensus can be expected. Thus, the volatility level is a very useful indicator for the overall level of consensus among traders. Even if the fundamental value changes and the stock price converges to a new level, the volatility measure then adapts this change and increases. Once several changes of the fundamental value occurs, the volatility increases and indicates a high level of uncertainty. Hence, a stock price' time series with a high volatility can be interpreted that traders did not come to a consensus and, thus, the prediction of this stock is uncertain compared to a stock showing low volatility. For the measurement of volatility of stock j, the standard deviation (s_j) is used, which is depicted in Equation (5.1), where E_{ij} denotes the observed values in a time serie j, M_j denotes the average value of it and n_j denotes the number of observations.

$$s_j = \sqrt{\frac{\sum_{i=1}^{n} (E_{ij} - M_j)^2}{n_j - 1}} \tag{5.1}$$

Several patterns of time series can be identified. Experiment data from Chapters 4 and 5 were analyzed and the following patterns could be identified.

- **Up** —
  Stock prices rise over time.
- **Down** —
  Stock prices fall over time. E.g., in Figure A.1(d).

- **V** —
  Stock prices fall down and then rise again – and vice versa, e.g., Figure A.4(a). The V-characteristic can be broader or narrower. Figure A.4(a) is an example for a narrow V pattern whereas Figure A.4(c) is an example for a broader V pattern. This pattern also applies to time series where the price rises first and then decreases.
- **ZigZag** —
  Stock prices alternate in periods of rising and falling. E.g., Figure A.3(a), Figure A.3(d) or Figure B.10.
- **Plateau** —
  Stock prices remain at a plateau and do not rise or fall heavily. E.g., Figure B.7 or Figure B.10.

Several patterns may occur in combination with other patterns. In order to classify these patterns to a time series, it can be determined if a sequence of trades is observable. One way is to analyze the sequence of buy or sell transactions. If a majority of consecutive buy or sell transactions moved the stock price into one direction or if the sequence is of minor impact, the interpretation of it can be used for the classification.

The classification of time series into the proposed patterns is the first step in order to derive a level of confidence which can be provided to decision makers in a single measure. Therefore, each pattern shows certain characteristics regarding the number of trades as well as the volatility. The number of unique traders can also be interpreted in this context. However, it does not change the course of the stock price and is therefore disregarded. Hence, the confidence score considers the number of traders as well as the volatility of time series. Table 5.8 shows the expected characteristics of the proposed patterns.

Table 5.8: Characteristics of Patterns for Time Series

Pattern	# of Trades	Volatility
Up	medium/high	medium
Down	medium/high	medium
V	high	high
ZigZag	high	high
Plateau	low/medium/high	low

From a decision maker's point of view, stock prices showing a low volatility and a medium or high number of trades seem more confident as a representation than stock prices showing high volatility and a low number of traders. Confident stock prices can be expected for patterns like Plateau, Up and Down where the level of uncertainty is moderate. In highly volatile time series, one cannot expect that traders agree in a consensus and, therefore, decision makers have to interpret it carefully. In extreme cases, trades can be conducted by only one trader. Therefore, the total number of unique traders is also important to decision makers and indicates how many traders are involved in the price discovery process. In both investigations in Sections 5.3.4.2 and 5.3.4.3, the number of unique traders does not add further information since the number of unique traders is on average equal in each stock. Table 5.9 illustrates the classification matrix.

Table 5.9: Classification Matrix

		Volatility		
		low	medium	high
# of Trades	low	c	d	e
	medium	b	c	d
	high	a	b	c

With this classification, contracts can be tagged based on their combination of volatility and their number of trades. In the following, the number of trades and the volatility is equally weighted. Depending of the dataset, input parameters can be weighted based upon their importance. For example, if prices show balanced volatility, the number of trades can be prioritized by a weighting factor. In addition, the classification can be conducted for several periods of the market duration, for instance, the last two trading days, the last trading week and so on to put more influence on recent periods which cover more information as mentioned earlier. This classification also maps both input parameters to a number, for instance 1-5, where 1 is represented by the green color and 5 is represented by the red color. One can also use other or more (weighted) input parameters for the classification like traded volume, but this depends on the type of data and is to be decided individually. In this work, the two described input parameters are used. Equation 5.2 shows the categorization function where the numbers are associated with the colors as follows: a → dark green, b → light green, c → yellow, d → orange, e → red.

$$f(\text{Volatilität, Anzahl Transaktionen}) \rightarrow (a\ (++), b\ (+), c\ (\bigcirc), d\ (-), e\ (--)) \quad (5.2)$$

In order to assign a confidence score to stocks, the input data is characterized separately. First, stocks are sorted by the number of trades in a descending order. Second, one third of stocks with the highest number of trades is marked “high”, the second third with a medium number of trades is marked “medium” and the third with the lowest number of trades is marked with “low”. Then, the same characterization is conducted with the second input parameter. As mentioned, low volatility is in this investigation considered as more confident than high volatility. Thus, high volatility is decreasing the confidence score. The result is the combination of rankings which is described in Table 5.9. For instance, the stock with a high number of trades and low volatility is sorted into the dark green cell on the lower left marked with character “a” and so on. In the following section, the results from the experiment introduced in Chapter 4 serve as the evaluation dataset in order to test the classification before the dataset in this chapter is finally categorized and discussed.

Another approach to map the input parameters to the classification numbers is the usage of Fuzzy Logic[13]. In some cases, the mapping of stocks cannot be

[13]For details about Fuzzy Logic refer to Klir and Yuan (1995) and http://plato.stanford.edu/entries/logic-fuzzy

determined precisely following the mapping mentioned in Equation 5.2. Two stocks can be very similar regarding their number of trades and volatility, but one of them is characterized as a "b" and the other as "c". The mentioned mapping presumes that stocks can be characterized precisely. Since the characterization is based on relative values of the whole dataset and does not refer to an absolute fixed point for volatility and number of trades, stocks can range between two numbers. Thus, Fuzzy Logic can be applied whenever a mathematical correlation between input and output parameters cannot be exactly described. In contrast to "crisp logic", where parameters are classified exactly based on binary decisions, a fuzzy approach classifies input parameters approximately rather than accurately. In this work, the application of Fuzzy Logic is not described and is left as future work. In addition, the characterization can also be conducted via Neuronal Networks[14], which are also promising to be investigated. In the following, the evaluation of the confidence score is described.

5.3.4.2 Evaluation of the Confidence Score

As described in Section 5.3.4.1, the categorization of stocks based on volatility and trading activity measures provides valuable additional information about how stock prices evolved. The development of the categorization was necessary since the results of the field experiment at EnBW cannot be paid out according to actual outcomes of events, which do not occur in innovation contexts. Therefore, decision makers need additional information of how "confident" a stock price is. In order to evaluate the categorization presented in Section 5.3.4.1, the dataset from the experiment introduced in Chapter 4 is used since the characterization can be compared to the real outcomes.

In order to evaluate if the confidence score operates confidently, an analysis of characteristic patterns derived from the observable patterns mentioned in Section 5.3.4.1 will be described in the following. Table 5.10 illustrates the input data. In the pattern column, the name of the pattern as well as a thumbnail of the price evolution is shown.

Table 5.11 illustrates the application of the test patterns according to the confidence score. In Section 5.3.4.3, the application of the confidence score is conducted for the EnBW dataset.

As one can see, the confidence score classifies each pattern into a cell in the matrix. The confidence score classifies all input data relative to the whole dataset, which means that a red classified pattern is the "worst" in the classification, but does not need to be absolute worse. Therefore, the confidence score identifies "confident" stocks in a given dataset.

In order to apply the categorization to a real world dataset, the data of the group phase from the experiment described in Chapter 4 was taken. Stock prices were used

[14] Neuronal networks provide a classification which is to be learned based on a training dataset. Once a neuronal network is trained, it is capable of processing input parameters to a certain output based on the logic covered in the training dataset. For example, time series with known volatility and known number of trades can be combined to a training dataset to set up the neuronal networks. Afterwards, new datasets can be processed via the neuronal network in order to obtain a classification matrix according to Table 5.9.

Table 5.10: Evaluation of the Confidence Score

No.	Pattern	Volatility	# Trades
1	Plateau 1	2,24	65
2	Plateau 2	0,00	30
3	Plateau 3	2,24	100
4	ZigZag 1	4,00	110
5	ZigZag 2	3,00	70
6	ZigZag 3	2,00	40
7	V 1	3,74	60
8	V 2	4,58	80
9	V 3	5,48	50
10	Cont. 1	3,16	55
11	Cont. 2	3,54	75
12	Cont. 3	2,35	40

Table 5.11: Classification Matrix - Test Evaluation

		Volatility		
		low	medium	high
# of Trades	low	2, 6	12	9
	medium	1	5, 10	4, 7
	high	3	11	8

from the beginning of the group phase till the outcome of the event was available. Furthermore, the input data for the classification was clustered into four periods which were the last trading prices, the average last trading day, the average last two trading days as well as the last average trading week. The prices during the last trading day are used in multiple clusters and, thus, get more weight in the overall classification which calculates the average of all used periods. This is to ensure that the development of earlier trading days is also considered and, thus, not only the last trading activities are used. As already mentioned, considering only the last trading day may lead to an inappropriate representation of the evolution of prices as it is in case of Figure 5.12. The results of the categorization are shown in Table 5.12.

Table 5.12: Classification Matrix - Evaluation 1/2

		Volatility		
		low	medium	high
# of Trades	low	2, 12	1, 3, 8	
	medium	14, 15	6	5, 7
	high	10	4, 9	11, 13, 16

The categorization in Table 5.12 follows the same rules as described in Section 5.3.4.1. Stocks with high/medium/low volatility as well as high/medium/low trading activity are categorized in a matrix similar to Table 5.9. After the stocks were put into the matrix based on the classified input parameters, the ranking of all stocks after the group phase is colored according to the matrix shown in Table 5.13.

Table 5.13: Classification Matrix - Evaluation 2/2

Stock	Winner (Last Price)	Final Round
12	95.52	✔
3	90.00	✔
15	80.00	✔
9	64.41	✔
16	61.24	✔
5	58.68	
11	54.00	✔
1	52.12	
6	43.20	
7	29.94	✔
13	29.56	
14	25.95	✔
8	25.08	
2	21.00	
10	08.02	
4	00.04	

As one can see, traders were right in their forecast of which team will reach the final round in 6 out of 8 cases. The dark green color indicates that traders assessed stocks with the lowest volatility and the highest number of trades and so on. The red color indicates that the evolution of stock prices was based on extremely high volatile trading activity and a very low number of trades, which was not the case in this dataset. The two light green stocks in the third and fourth place indicate that these stocks were traded with low or medium volatility and at least medium number of trades which indicates that traders were confident that these teams will reach the final round. In case of stock 10, traders were very confident that the team will not reach the final round. In this case, Switzerland was the only team which did not win one of the first two matches and therefore dropped out of the tournament early. In case of stock 4, traders showed a strong consensus that this team will drop. Stock 14 is also classified as confident whereas it was predicted wrong. In this case, traders constantly misinterpreted the likelihood that Turkey will make it although they won two of their three group phase matches. Stock 3 is also characterized as less confident, although the stock price is extremely high and therefore, traders were confident that this team will make it to the finals but were not sure about the exact likelihood. All charts of the field experiment are depicted in Appendix A, Figures A.1 - A.6.

As mentioned, the evolution of stock prices shows different patterns over time. For example, Figure A.1(d) showed a consensus that Switzerland drops out of the group phase and shows a downward slope of the stock price which matches the "Down"-pattern as described in Table 5.8. In case of Spain, the patterns follow a downslope at the beginning once Spain won the second game and an upslope afterwards which is similar to the "V"-pattern described in Table 5.8. In order to add such information about the evolution of prices, the characteristic of stock prices during the group phase have to be analyzed to add further information in addition to the colors. The examples of Switzerland and Spain indicate that the characteristic of stock prices reveals, if traders showed a consensus during the market period or if they thought that the probability of reaching the final round changed heavily. Heavy changes in the estimation of traders result in high volatility in trading activity. Thus, the confidence score is capable of characterizing stocks according to their volatility and the number of traded shares.

Stocks close to a price of 50 currency units indicate that this team is close to reach the final round. Therefore, stocks ranging in the middle of the ranking are hard to interpret. Thus, additional information can be added via the analysis of how this price formed over time. Hence, one has to regard the evolution of stock prices in terms of how many traders caused a change and how stock prices moved up or down in a certain period of time. Altogether, traders may either predict correctly with a high level of confidence or wrong with a high level of confidence whereas the second case is fatal. On the other hand, stocks showing low confidence reveals that traders do not agree about the likelihood of the events. Thus, low confidence should also be treated carefully. In the following, the confidence score is applied to the dataset from the EnBW experiment introduced in this chapter.

5.3.4.3 Application to the EnBW Dataset

For the classification, six periods were chosen to be used in order to put weight on the periods close to the end of the market which comprise actual information as stated in Section 3.1.1. The periods are defined as follows:

- 1 day before market close (t_{-1})
- 7 days before market close (t_{-7})
- 14 days before market close (t_{-14})
- Period: 1 day to market close ($t_{-1}; t_0$)
- Period: 7 days to market close ($t_{-7}; t_0$)
- Period: 14 days to market close ($t_{-14}; t_0$)

The first three periods are based on daily average values for the number of trades and standard deviation. For the second three periods, the volatility as well as the number of trades where humans were involved have been calculated on an average basis. As mentioned, several periods build the basis for the analysis to capture the trading history and to put weight to the periods close to the end of the trading period.

In order to combine values like standard deviations, the relevant transaction prices were also tested for stationarity. A stationarity test indicates how the means and variances of time series change over time. If time series are stationary, it can be assumed that trading prices show a stable course over time and can therefore be expected to be representative for a certain time. As seen in Figure 5.12, the trading price changed rapidly on the last day. On the days before the market ended, the trading price was stable and did not change noticeably. The results of the stationarity test show that all contracts are stationary based on their trading sequence. Hence, the time series can be used for further analysis. The test was conducted with a Augmented Dickey-Fuller test and a Phillips-Perron test (Dickey and Fuller 1979; Phillips and Perron 1988).

The results of the investigation for volatility and the number of trades are depicted in Table 5.14. The four most volatile shares are colored red, the four medium volatile shares are colored yellow and the four shares with the lowest volatility are colored green. Regarding the number of trades, the four most traded shares are colored green, the four medium traded shares are colored yellow and the four lowest traded shares on average are colored red.

Table 5.14: Volatility and # of Trades: Shares can be categorized based on their characteristics of volatility and the number of how often they were traded. Often traded shares are colored green, medium traded shares are colored yellow whereas lowest traded shares are colored red. In case of volatility, shares with the highest volatility are colored red, medium volatility is colored yellow and low volatility is colored green.

Stock	Volatility	# of Trades
1	20.71	52
2	4.54	97
3	3.30	42
4	4.17	21
5	17.00	25
6	7.77	58
7	0.98	28
8	3.90	74
9	0.45	7
10	8.24	57
11	5.90	11
12	2.59	48

Table 5.15: Classification Matrix

		Volatility		
		low	medium	high
# of Trades	low	7,9	4,11	5
	medium	3,12		1
	high		2,8	6,10

The results of the classification are applied to the classification matrix and are shown in Table 5.15. Shares with a high volatility marked in red color in Table 5.14 are categorized in the right column named "high". If the volatility was low, indicated by green color, the share is categorized in the left column named "low". The same applies to the number of trades in Table 5.14. For instance, a high number of traded shares indicated by green color is categorized in the last row whereas a low number of traded shares marked with red color is categorized in the first row named “low” in Table 5.15. The result of the confidence score are transferred to the market results which are usually delivered to decision makers and are shown in Table 5.16.

Table 5.16: Decision Makers vs. Enterprise Information Market - enhanced

Rank	Decision Makers	Information Market
1	Web 2.0 Poster	All in one
2	xing@enbw.com	MEREGIO Platform
3	All in one	Web 2.0 Poster
4	Intelligent Calendar Management	xing@enbw.com
5	Twitterinfo	Parallel Document Processing
6	Mobile Metering	Hardware Inventory
7	Parallel Document Processing	Mobile Metering
8	MEREGIO Platform	Home Automation
9	Home Automation	New Contact Networking
10	Digitizing Business Cards	Intelligent Calendar Management
11	Hardware Inventory	Digitizing Business Cards
12	New Contact Networking	Twitterinfo

As one can see, shares with a high volatility and a low number of shares can be easily identified. The ranking is based on last transaction prices and with the colors, it provides additional information to executives and decision makers about how “confident” prices are in relation to the remaining contracts. The ranking based on last transaction prices was chosen since last transaction prices are assumed to comprise the latest available information before the market was closed. The line between the fifth and sixth rank indicated the initial price of contracts. Contracts above this line increased their price and vice versa. It can be concluded, that traders were confident that contracts ranked 7 and 8 are below the issued price and contracts ranked 2 and 4 are above the issued price. Green colors indicate that the number of trades was high and volatility was low in relation to other shares. In contrast, the contract ranked 10 showed a low number of trades and a high volatility. Therefore, traders were either not able to assess this innovation alternative or several traders did not come to a consensus which lead to high volatility. This indicates that decision makers have to assess results carefully which are “less confident” based in employees’ assessment.

In summary, the results proposed in Table 5.7 can be enhanced and evaluated with the introduced confidence score. The results shown in Table 5.16 reveal that the ranking comprises two middle valued contracts (yellow) and two positive valued contracts (green) within the first four ranks. Altogether, the confidence score provides additional information to decision makers about the confidence of traders’ assessments. In future work, the refinement of the confidence score is promising in order to include additional input data like traded volumes or detailed results from a lead user analysis in Equation (5.2) and to provide even more sophisticated characterization results, e.g., through the application of pattern recognition algorithms.

5.4 Conclusion

The results of this section show that Information Markets motivated employees in using them and, thus, they traded continuously (c. Section 5.3.1.1). Furthermore, market participants approved the method of Information Markets and used it frequently (c. Section 5.3.2.2). The results of a survey among participants indicate that most of the participants assess the method of Information Markets as a good one (cp. Table 5.11). Table 5.17 summarizes the results based on the design objectives stated in Section 5.2.

Table 5.17: Summary of Results

Design Objective		Result
1 a)	Trading activity equally spread over time	●
1 b)	Traders are active during market duration	●
1 c)	Employees are motivated in using the EIM	◐
2 a)	Employees assess the method of EIM positively	●
2 b)	The EIM is accepted and actively used	●
2 c)	EnBW can better assess innovations via EIM	●
3	Results of the EIM do not differ to Experts	●

● statisfied, ◐ partly satisfied, ○ not satisfied

Moreover, the results of Section 5.3.2.2 show that the results of the Information Market and the expert panel overlap in three innovations, which indicates that in this field experiment the results differ only slightly between the EIM and the decision makers. The situation could have been different, if the market results differed heavily from the results of the expert panel and hit case (2) or (3) described in Table 5.6. Then, the decision makers have to take further actions like hiring an external consultant or involve other people capable of providing an additional independent ranking. Another action could be to invite the identified Lead Users described in Section 5.3.1.2 to an expert round and discuss their motives.

After the market closed, the results were discussed with decision makers. Finally, two innovations were implemented at EnBW. The implementation of “Web 2.0 Poster” was finished within the second half of the year 2009. “xing@enbw.com” won one out of three innovation vouchers worth 25.000 € in an internal award procedure and is going to be implemented shortly. In total, ten innovation contenders applied for the three vouchers. Therefore, the results of the market supported the results of the decision makers strongly.

Figure 5.13 shows, which success factors are mostly relevant for change management (Jørgensen et al. 2008). The three top categories can be addressed with an EIM. Interestingly, the top aspect is the sponsorship of the top management. In Section 5.3.1.2, executives were identified as lead users. If the top management is involved in innovation processes as lead users, this can be interpreted as a very strong sponsorship and shows the commitment of the top management.

The second success factor, named “Employee involvement” can also be addressed with Enterprise Information Markets. Employees were invited to join the market,

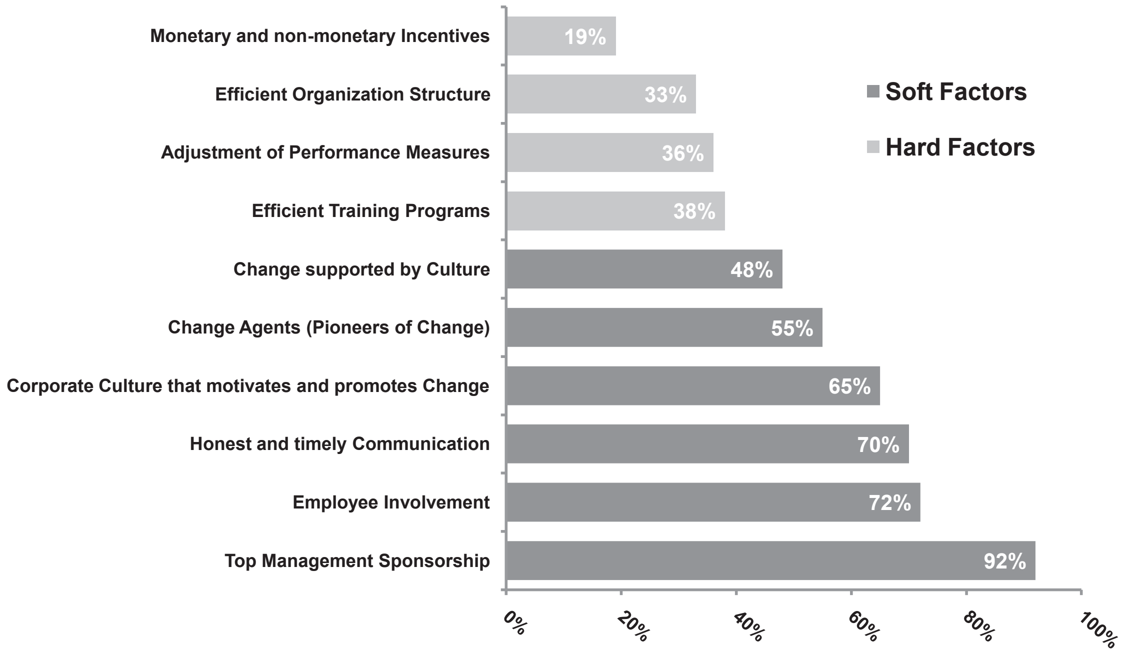


Figure 5.13: Success Factors of Change Management
Adapted from Jørgensen et al. (2008)

if they were interested in providing their estimations to the market. As shown in Section 5.3.1.1, they traded continuously and actively over the market duration. Furthermore, honest and timely communication is another essential success factor in change management. The market can be considered as communication method, as described in Section 3.2.2, because employees can "communicate" their estimations through their trading activity. Often, employees do not communicate their true estimations because they may fear consequences from their managers, if they have "negative" information. In Information Markets, participants are anonymous and may fearlessly communicate even "negative" information.

Often, the success of change processes is directly connected with the culture of a company, as described in Section 2. EnBW uses Information Markets in order to involve employees actively, which indicates a very open company culture. Often, employees cannot be involved in innovation processes due to complexity aspects in managing thousands of employees via questionnaires or online surveys. Information Markets are a very scalable method to involve a large number of employees efficiently. The market mechanism aggregated new information continuously and employees participated actively, which indicates a culture that motivates employees to participate and involves them in innovation processes.

Altogether, the Information Market was a new way for the EnBW to involve their employees in innovation processes and provide a sustainable method after the innovation workshop. The experiment catches on so that the EnBW wants to have another Information Market. The very valuable knowledge of employees is now a key main pillar in their innovation process. Therefore, besides the positive feedback in the survey, the next Information Market will be as successful as the one introduced in this chapter and may confirm the results shown in this work.

Part III

Finale

6 Conclusion

In this thesis, Information Markets were introduced in innovation contexts as a method for the assessment of innovation alternatives. The easy integration of employees, customers and consultants as well as the continuous forecasting and information aggregation capabilities of Information Markets are promising to deliver valuable information to decision makers in companies. But Information Markets may suffer from low trading activity and, thus, illiquid Information Markets may lead to inappropriate results. Hence, the usage of automated market maker mechanisms was investigated in order to foster useful results. Two main objectives were investigated in this thesis. The main research questions stated in Section 1.1 can be briefly summarized as follows whereas R1 and R2 amalgamates whenever small-sized Information Markets are threatened by illiquidity.

> R1: Do Information Markets show more trading activity, increased accuracy, less error and higher information efficiency utilizing automated market makers?

The impact of automated market maker mechanisms in Information Markets was evaluated in a field experiment predicting the outcomes of soccer matches. Two identical markets were set up, whereas one market employed an automated market maker mechanism while the other one did not. The results of both markets were compared to the outcome of soccer matches during the European Soccer Championship in 2008. The result of the comparison indicated that the overall accuracy of the automated market maker market was equally accurate as betting odds from wetten.de and more accurate than forecasts derived from the FIFA world ranking. Compared to the parallel market without market maker mechanisms, the trading activity was higher and the market itself showed increased information efficiency.

Based on the results of R1, another field experiment was set up to investigate the application of Information Markets for the assessment of innovations, which was addressed by R2.

R2: How to design and operate Information Markets for innovation assessment in companies?

The usage of Information Markets in companies is a delicate field of application. The employment of Information Markets influences the business culture and therefore, it has to be investigated how Information Markets can be designed and operated in order to be accepted by employees as well as decision makers. The results of the field experiment in an innovation context at EnBW Baden-Württemberg showed, that employees accepted the Information Market as a valuable tool for the assessment of innovations. Furthermore, the market results aligned with the results of the survey for decision makers. This indicated that the innovation alternatives were assessed coherently. Altogether, the proposed market design as well as the design of the automated market maker, as a result of R1, turned out to be useful and enabled the success of the field experiment.

In the following, Section 6.1 summarizes the key findings during the course of this work. Afterwards, Section 6.2 discusses the limitations of the approach. Section 6.3 gives an outlook on complementary research and future work.

6.1 Summary of the Key Findings

In this thesis, Information Markets were introduced as a method for the assessment of innovations in an enterprise context. Up to now, only a little number of research articles reported findings and experiences from this field of application. While the challenges, the functioning as well as the implications for the application of Information Markets in enterprise contexts are not completely understood, so far this work provides further findings for two application scenarios of Information Markets. First, the performance of Information Markets in low liquidity situations was analyzed via a field experiment during the European Soccer Championship in 2008. With the findings of this experiment an additional field experiment was conducted in an industry innovation context at EnBW Baden-Württemberg in order to investigate how Information Markets perform in the assessment of innovation alternatives. The presented work provides the following contributions:

1. The results of the field experiment for small-sized markets provide evidence that Information Markets lead to more accurate results via the employment of an automated market maker mechanism compared to small-size markets without an automated market maker functionality. It furthermore analyzed the impact on trading activity and information efficiency and showed that the trading activity as well as the forecast accuracy increased with the automated provisioning of liquidity. Furthermore, market efficiency increased whereas the forecast error decreased.

2. This thesis provides evidence that Information Markets can be used in industrial innovation contexts. Employees accept Information Markets as a method for the aggregation of individual expectations and beliefs about innovation alternatives. Moreover, employees and decision makers' expectations can be combined in order to get an aggregated reflection of estimations. Information

Markets motivate employees to reveal their information and, thus, employees assess the method of Information Markets as appropriate to evaluate innovations alternatives.

After the introduction in Chapter 1, Chapter 2 emphasized the usage of Information Markets for innovation assessment objectives. The state-of-the-art in Innovation Management was described and the benefit of group decisions via Information Markets against individual decisions was shown. The application potential of Information Markets to support the communication of stakeholders in a market mechanism was illustrated. Furthermore, traditional methods for decision making commonly used in innovation contexts were compared to Information Markets, whereas advantages of them, e.g., the involvement of stakeholders and the integration of employees, as well as challenges regarding the business culture were highlighted. In addition, it was explained that Information Markets can be applied in inter-organizational innovation contexts (Business Networks) where "open innovation" enables their implementation and, thus, support (group) decision making even across companies boundaries.

In order to provide a comprehensive introduction of market systems, Chapter 3 highlighted the fundamentals of markets, e.g., the efficient market hypothesis and trader's motives. Market engineering as a research direction was illustrated to support market designers to identify vital aspects to be considered while setting up Information Markets. In addition, the functionality of Information Markets in contrast to financial markets was described. Relevant design parameters like the design of contracts or the selection of traders were discussed and the utmost importance to design contracts carefully was highlighted in order to keep them easy to understand and intuitive to interpret. Incentive schemes need to be clearly defined to allow traders the interpretation along the market objective and to motivate them. Furthermore, to assess the outcome of Information Markets, useful measures to describe market liquidity and information efficiency were introduced. Moreover, mechanisms for automated market making were illustrated and compared against each other considering their practicability, transparency and liquidity provision capability. In essence, a CDA mechanism with an automated marker maker functionality was chosen to be implemented in the field experiments in Chapters 4 and 5. In order to show futurity application potential of Information Markets in inter-organizational contexts, the usage of Information Markets as an essential part of innovation management in the TEXO research project was described as well.

In Chapter 4, the results of a field experiment to investigate low liquidity markets were described. Therefore, the experiment design was highlighted including the decisions on market design and the used market maker mechanism. After the introduction of descriptive statistics, hypotheses were stated in order to investigate research question R1. The first research hypothesis analyzed the trading activity of traders during the experiment. The results of the comparison of both markets showed, that the trading activity in the market maker market was significantly higher compared to the non-market maker market. Moreover, the forecasting accuracy was also higher whereas the forecasting error was lower, which was investigated via according research hypotheses. The hypothesis concerning the information efficiency, which was measured via an arbitrage trading analysis, revealed that the market maker market showed a significant increase of information efficiency. Afterwards, a conclusion summarized the contributions of the chapter.

Based on the results of Chapter 4, the use of Information Markets in an industrial context was studied in Chapter 5. During a field experiment at EnBW Baden-Württemberg, an Information Market was implemented in order to assess innovation alternatives by employees. At the beginning of the chapter, the experiment design was described followed by design objectives for the investigation of research question R2. R2 was supported by three design objectives which were the analysis of trader's activity, motivation as well as the results of the Information Market compared to decision makers. It was shown that the trading activity was constantly observable. The most active trader did more than 1.000 trades during the experiment, which was not expected. Survey results as well as the trading activity showed that traders were motivated to use Information Markets, whereas they also perceive a non negligible effort. Since, the effort and the motivation of traders were negative correlated, this result indicated that further improvements of Information Market's usability would lead to a higher motivation. In addition, the result of the third design objective showed that the top three innovations from decision makers were also assessed within the top four innovation alternatives in the Information Market which indicated that employees as well as decision makers showed a coherent assessment. Moreover, a lead user analysis revealed that even executives were actively trading amongst the most active traders. Hence, executives showed their interest to use Information Markets for innovation assessment. The conclusion then summarized the contributions of Chapter 5.

6.2 Limitations of the Approach

In this work, field experiments were conducted in order to collect the results presented. Results of a field experiment, in contrast to laboratory experiments or simulations, are conducted in an uncontrollable environment where external effects influence the experiment results. In a laboratory experiment, external effects can be controlled. It may occur that the same market mechanisms in a repeated field experiment would leads to other results than reported in this work. Nevertheless, this work provides evidence that in both presented field experiments Information Markets produced appropriate results concerning the objectives of the market. Thus, the general applicability needs to be further evaluated via experiments and investigations.

In the field experiments presented, people participated and were supposed to reveal their true beliefs and expectations. In scientific literature, it is assumed that traders behave rationally and follow rational behavior patterns. But in reality, they sometimes do not, as reported in this work. In a field experiment as well as in financial markets, traders have individual motives, risk aversion levels and individual incentives which cannot be anticipated and regarded in the experiment design. Sometimes, these motives go beyond rationality and, therefore, several behavior patterns, e.g., those from noise traders, cannot be explained completely because some motives have not been covered by market models, yet (De Long et al. 1990). Effects of noise trading are normally counteracted by arbitrageurs. Hence, the results presented in this work may be afflicted in some parts due to trading behavior of noise traders while arbitrageurs were not quick enough to counteract. For example, one trader tried to raise the market price in the presented Information Market in Chapter 4 way beyond to what is rational.[1] Those effects were unfortunately reflected in the results. Other traders brought the price back to a normal level within several hours. In order to investigate behavior patterns or regard them in the results, several pre-tests have to be conducted to learn, e.g., risk aversion levels or motives of each individual trader, which is hardly feasible during a field experiment with only a few traders. The risk of losing traders by bothering them with mandatory questionnaires is to be balanced with the benefit of having them actively trading in Information Markets without knowing their motives exactly.

In this work, the automated market maker mechanism was designed to provide liquidity at any time in both field experiments. The intention was to show that even a simple automated mechanism fosters accurate trading activity and accuracy as well as information efficiency. The algorithms of the market maker employed reactive strategies and traders tried to play them. Therefore, the possibility of a distortion or manipulation of the markets cannot be fully eliminated. The focus of this work was to evaluate the impact of automated market making on Information Markets rather than to identify the optimal algorithm design. Hence, more sophisticated algorithms are promising to deliver even more robust results than reported in this work.

Furthermore, the payout of contracts in innovation contexts cannot be determined. Information Markets provide a snapshot of estimations and beliefs from traders. If a company has to decide which innovation they should go for, it is left unclear if the chosen one is most beneficial because not all innovations can be evaluated due to economic constraints. Thus, the results of the conducted field experiment were compared to survey results from decision makers in order to evaluate if the market results deviate from those of decision makers. In this context, the market results were inline with those of decision makers. As an alternative, it was intended to use an Information Market for experts in parallel to the market for employees in order to use the market results as payout function for the other market. Unfortunately, the market for experts could not be applied as a benchmark due to extremely low trading activity.

6.3 Complementary Research & Future Work

As stated in this work, Information Markets are used in Innovation Management frameworks, e.g., the TEXO research project. It is interesting to further investigate Information Markets in cross-organizational contexts. Nowadays, Business Networks are in their infancy and therefore, once these networks are more mature, they seem to be a promising field of application for Information Markets. Inter-organizational contexts offer a variety of opportunities for the application of Information Markets since companies are working together for the creation of value. Thus, Business Networks will become a promising field of application, not only for innovation assessment.

[1] The trader submits an order to raise the market price up to 5.000 currency units, whereas the maximum payout was 100 currency units.

Moreover, the field experiment at EnBW Baden-Württemberg will be continued in late 2010. The usage of Information Markets in order to integrate employees in innovation contexts at EnBW was considered as a very good approach and will therefore be repeated. The experience of the first experiment will be used to set up an improved Information Market. Hence, it is interesting to gain further evidence for the successful application of Information Markets in an industry context. Improved user interface techniques, adapted market maker mechanisms as well as revised incentive mechanisms will be investigated in order to confirm the success of the first experiment.

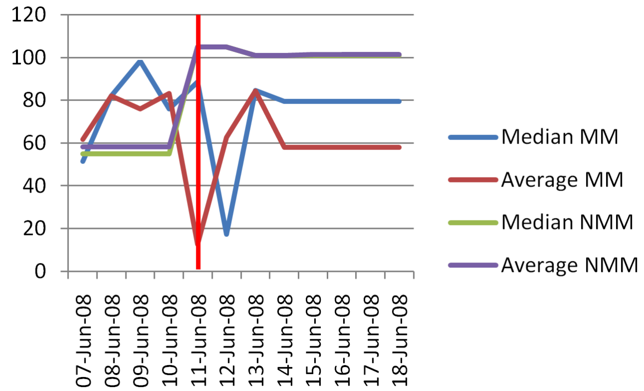
Furthermore, partly based on the insights of this thesis, Information Markets are currently under investigation in order to forecast economic indicators like Inflation, Exports, etc. (Teschner et al. 2011). It would be highly interesting to combine market results with other methods of forecasting like Delphi Studies, Surveys or historical data. Results from one method may serve as input for others and, thus, provide further information to participants. The implementation of several methods seems promising in order to compare results of different groups to assure consistent results among methods. In academia, several reports state that the combination of different forecasting methods improves the overall forecasting accuracy (Graefe et al. 2009). Thus, further investigation on the combination of different methods like Delphi Studies, Information Markets and historic social sentiments studies are interesting as well. For instance, one can analyze the effect of providing results from one method as input for another method and, thus, identify synergy potentials and reciprocal effects.

In Section 5.3.4, the results of the investigation about the confidence of traders (Confidence Score) in Information Markets is based on several input factors. It provides valuable additional information to decision makers. In future steps, the identification and interpretation of trading patterns can be improved, e.g., via pattern matching techniques (Pavel 1993; Duda et al. 2001). Moreover, the confidence score can be enhanced using additional input factors like trading volumes or results derived from single trader analysis of lead users. In addition, using a fuzzy approach for the categorization seems promising since in some cases one cannot exactly distinct if a stock is characterized more accurately in other cells of the confidence score presented in Section 5.3.4. In addition, fuzzy logic or a neural network approach may also provide appropriate characterization results of stocks in the confidence score. These promising approaches are capable of categorizing input values which cannot be characterized exactly and are, therefore, interesting to investigate in this context.

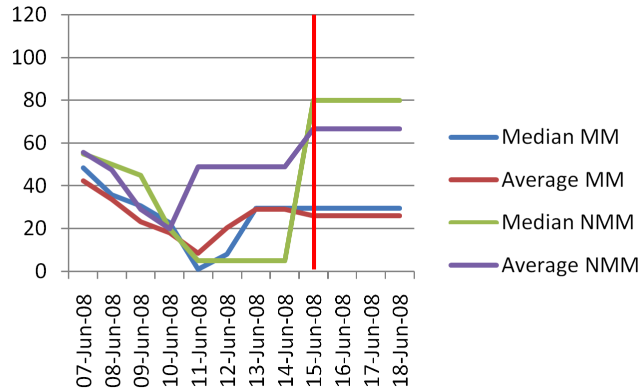
Concerning the investigation in low liquidity markets in Chapter 4, further experiments should be conducted in order to confirm the results presented in this work. Other types of incentive schemes as well as different variations of automated market maker mechanisms can be the focus of further research. In Section 3.3.4, several mechanisms for automated market making were introduced which can be compared to each other in order to analyze the benefits of each mechanism in detail.

This work investigated the usage of Information Markets in an innovation context in Chapter 5. In scientific literature, Information Markets were already used in new product development or sales forecasting contexts. It is interesting to identify other fields of application in enterprise contexts in order to support decision making. This fosters the need to further research incentive schemes. Experts seem to be reluctant to use additional methods besides their own established approaches. They notice Information Markets as a threat and not as an additional way to come to better decisions. Therefore, the further development of incentive schemes for industry usage is a very interesting field of research. For example, monetary incentives may have a different impact on managers compared to regular workers. Other incentives like leave days or awards may have a substantial impact on regular employees and managers.

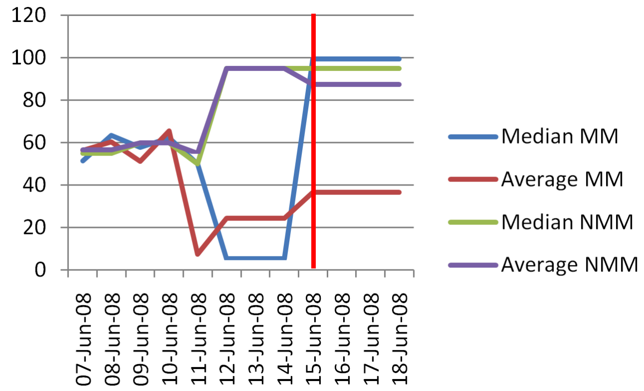
A Appendix to Chapter 4



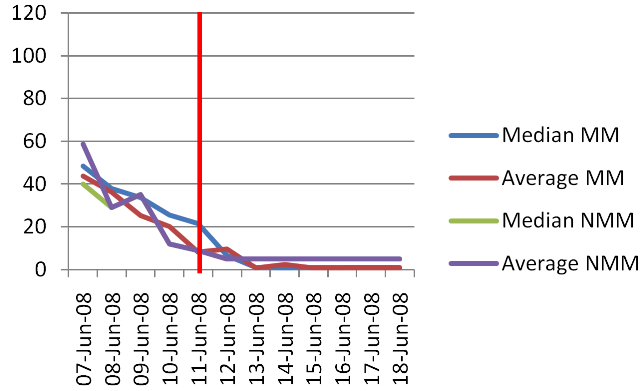
(a) Portugal



(b) Turkey

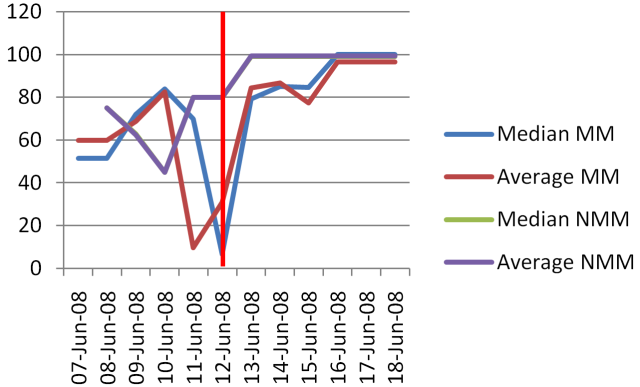


(c) Czech Republic

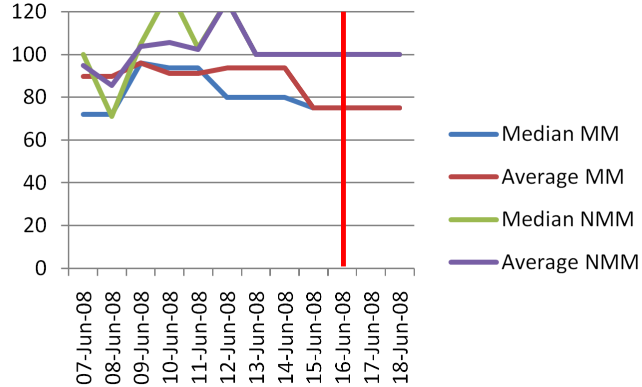


(d) Switzerland

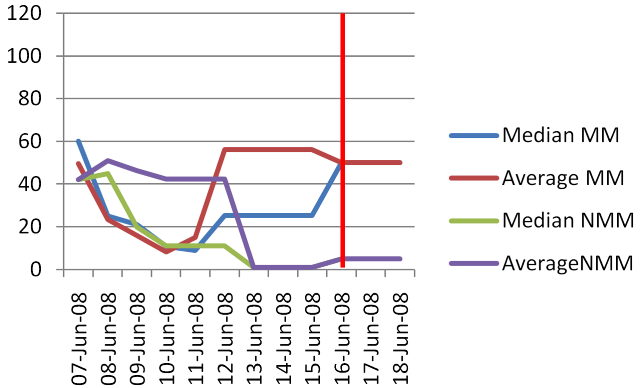
Figure A.1: Group Phase A



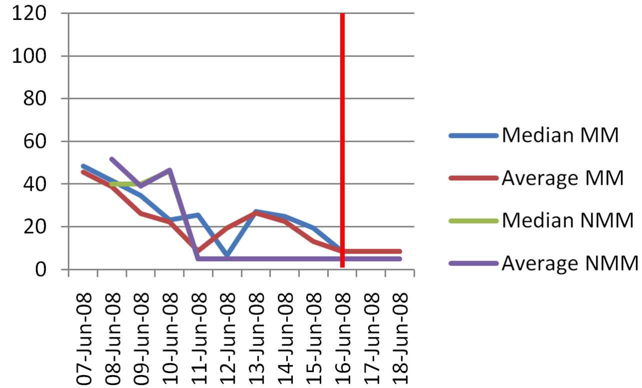
(a) Croatia



(b) Germany

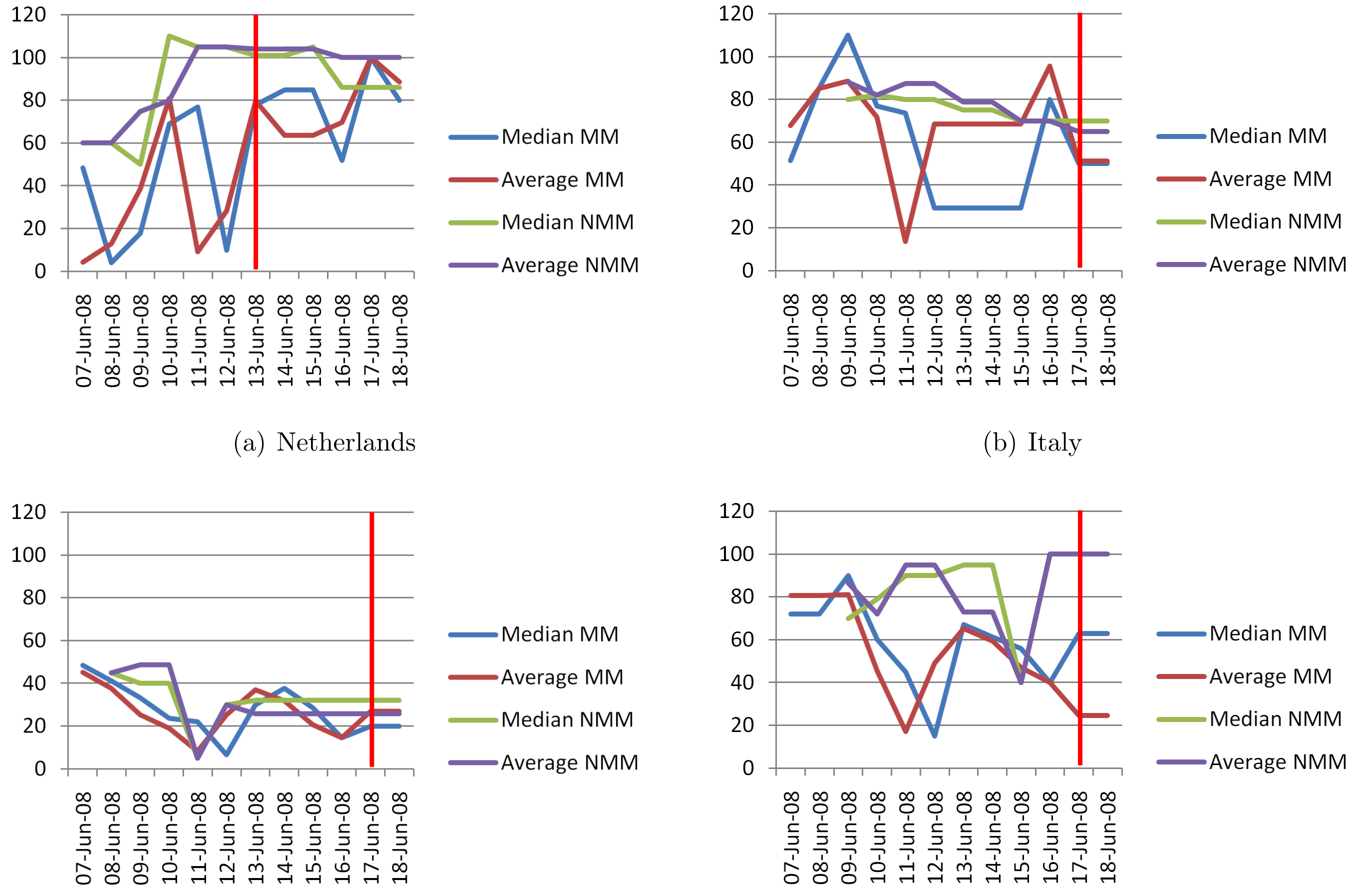


(c) Austria



(d) Poland

Figure A.2: Group Phase B



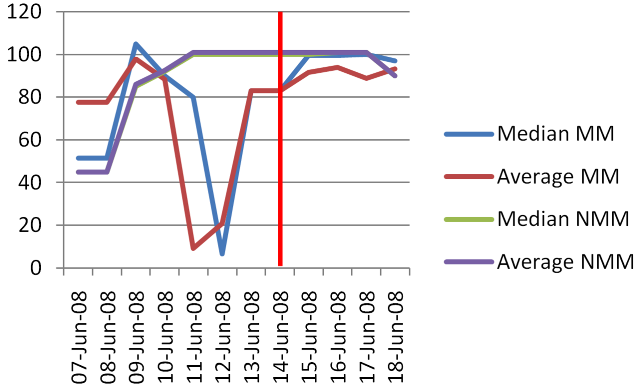
(a) Netherlands

(b) Italy

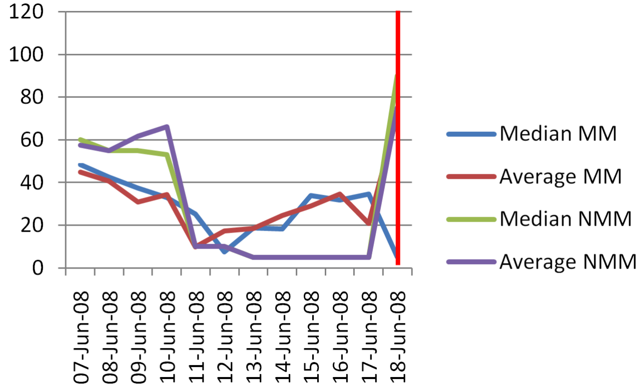
(c) Romania

(d) France

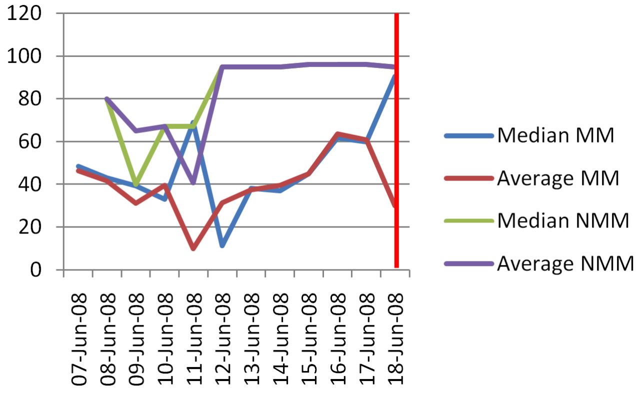
Figure A.3: Group Phase C



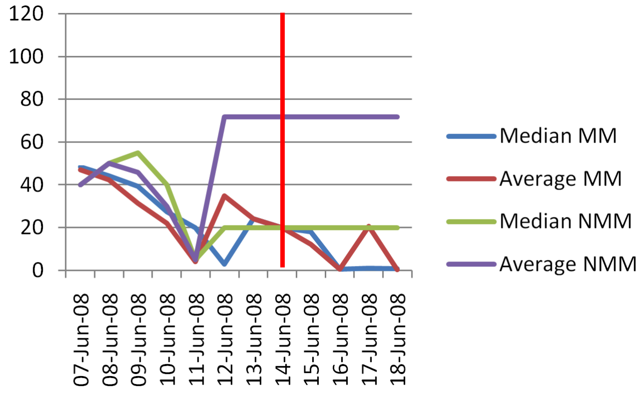
(a) Spain



(b) Russia

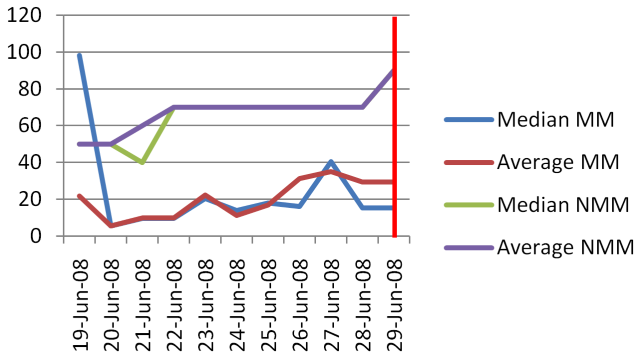


(c) Sweden

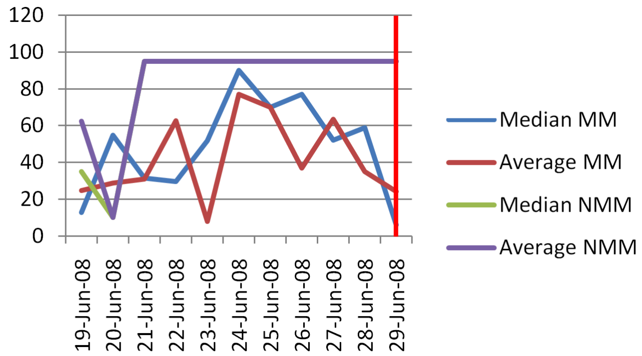


(d) Greece

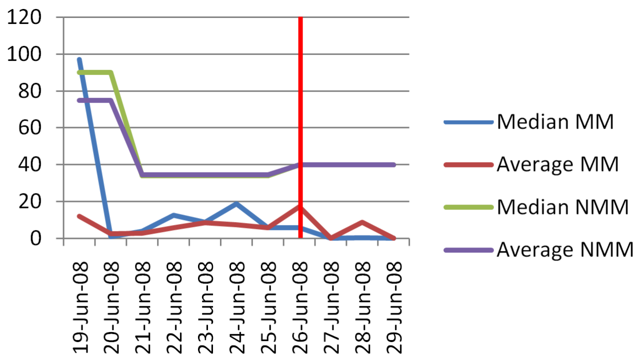
Figure A.4: Group Phase D



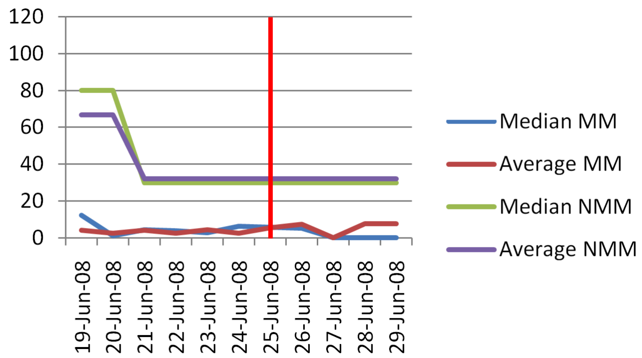
(a) Spain



(b) Germany

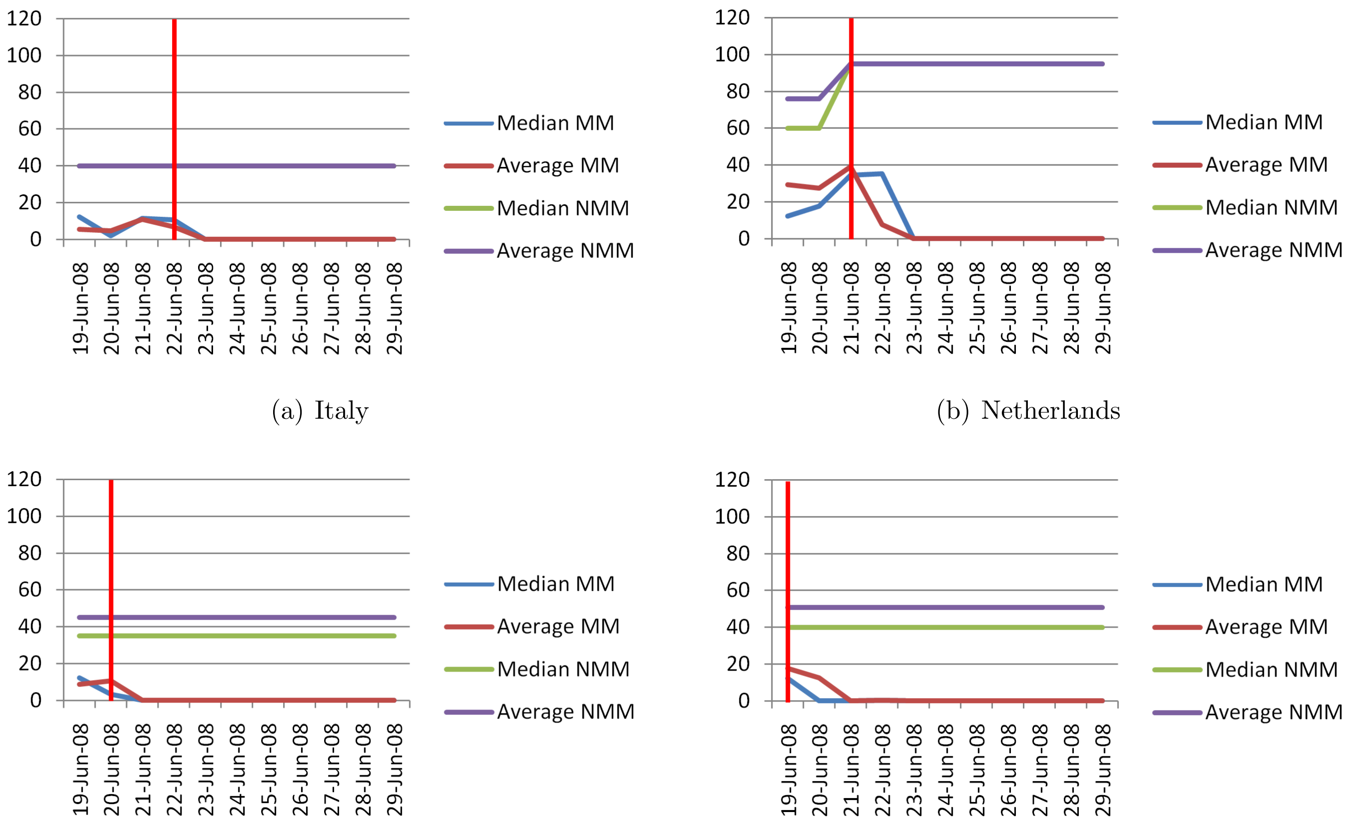


(c) Russia



(d) Turkey

Figure A.5: Finals 1/2



(a) Italy

(b) Netherlands

(c) Croatia

(d) Portugal

Figure A.6: Finals 2/2

In Figure A.7, the start screen of the Information Market is shown. On the left hand side, the navigation bar allows the quick access to further pages, for instance, the trading screen, the ranking or the depot. The navigation bar is visible at all times. In the center, the content of each page is displayed. In the following, figures of essential parts of the market system are zoomed in order to see the details, therefore, the figures themselves do not reflect the market system view completely. The market system supported German language.

Figure A.7: EM-Stoxx - Start Screen

Figure A.8 shows the ranking. Each trader is listed based upon his individual trading performance. It shows the user name, the depot value as well as the winning chance which is explained in Section 4.1.1.

Ranking

Rang	Benutzername	Gesamtwert	Gewinnchancen
1	pumuckl	683350	8.19 %
2	gido	446550	5.35 %
3	champion	297395	3.57 %
4	Franzi	223920	2.68 %
5	riordan	222600	2.67 %
6	nbo1	221950	2.66 %
7	hurricane	212648	2.55 %
8	siebel	203435	2.44 %
9	emstoxx	203170	2.44 %
10	Mauri	202995	2.43 %
11	jankra	201989.9	2.42 %
12	maxtrader	196400	2.35 %
13	Milenman	195000	2.34 %
14	apoplexdeluxe	193000	2.31 %
15	vagii	191000	2.29 %
16	nmay	190454	2.28 %

Figure A.8: EM-Stoxx - Ranking

Figure A.9 shows the SBT (AGB). The SBT had to be accepted by traders during the online registration process. The SBT state that any attempt to defraud, misbehavior, usage of automatic trading software etc. will be punished with market disqualification.

EM-Stoxx Market 2008

Allgemeine Geschäftsbedingungen für EM-Stoxx Market 2008

Die Teilnahme an der Prognosebörse Em-Stoxx ist kostenlos, setzt aber eine Registrierung voraus. Bei dieser Registrierung müssen die folgenden Daten vollständig und korrekt angegeben werden: Name, Vorname, Email-Adresse, Geschlecht, Jahrgang, Herkunftsland und Adresse. Die Teilnehmer garantieren mit ihrer Registrierung für die Richtigkeit aller bei der Registrierung gemachten Angaben. Teilnahmeberechtigt sind alle Personen über 18 Jahre unter Anerkennung dieser Allgemeinen Geschäftsbedingungen. Jede Person darf sich nur einmal bei EM-Stoxx registrieren. Der von den Teilnehmern gewählte Login-Name erscheint auf der Website in der Bestenliste und anderen Auswertungen.

Der Betreiber speichert die für Betrieb und Nachvollzug des Handels notwendigen Daten. Die Daten werden nicht an Dritte weitergegeben. Dritte in diesem Sinne sind alle Unternehmen und Personen, die nicht als Betreiber von EM-Stoxx Market 2008 deutlich genannt werden. Der Marktbetreiber haftet nicht bei Ausfällen des Servers und technischen Funktionsstörungen.

Das Recht, jederzeit ohne vorherige Ankündigung Änderungen oder Ergänzungen am bestehenden Angebot vorzunehmen, ist dem Marktbetreiber vorbehalten. Der Betreiber behält sich das Recht vor, die Sportbörse jederzeit abzubrechen. Die Verwendung jeglicher Art von automatisierten Vorgängen wie beispielsweise Scripts zur Manipulation der Sportbörse ist untersagt.

Der Betreiber behält sich das Recht vor, Teilnehmer zu disqualifizieren, die gegen diese Teilnahmebedingungen verstoßen. In solchen Fällen können Gewinne auch nachträglich zurückgefordert werden. Teilnehmer können temporär gesperrt werden, wenn ein Verdacht auf Manipulation besteht. Sachpreise können nicht in Bar ausgezahlt werden und sind nicht auf andere Personen übertragbar.

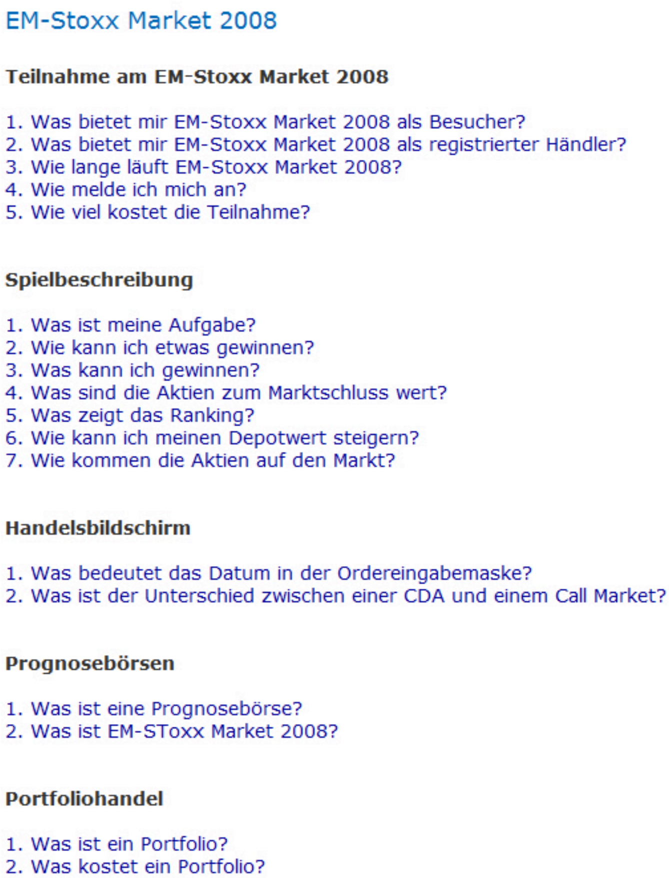
Es besteht kein Rechtsanspruch auf Teilnahme.

Die besten Händler sind nicht automatisch die Gewinner der Sachpreise, über die entgültige Verteilung selbiger entscheidet das Los.

Mitarbeiter des Instituts für Informationswirtschaft und -management (IISM), Universität Karlsruhe (TH), dem Forschungszentrum Informatik (FZI) und deren direkte Angehörige sowie Mitarbeiter des Karlsruhe Service Research Institute (KSRI), sowie deren direkte Angehörige sind genau wie die Mitarbeiter anderer am Spiel beteiligter Organisationen und Unternehmen teilnahme- aber nicht gewinnberechtigt. Die Veröffentlichung der mit Hilfe von EM-Stoxx Market 2008 erstellten Prognosen zu kommerziellen oder publizistischen Zwecken bedarf der Zustimmung und ggf. Vereinbarung mit dem Betreiber. Die Aktion unterliegt dem Recht der Bundesrepublik Deutschland. Der Rechtsweg ist ausgeschlossen.

Figure A.9: EM-Stoxx - Standard Businees Terms (SBT)

In Figure A.10, the FAQ are shown. In the FAQ, frequently asked questions were stated. Every question was linked to a section with answers in order to support traders to get familiar with the functionalities of the market system, quickly.


EM-Stoxx Market 2008

Teilnahme am EM-Stoxx Market 2008

1. Was bietet mir EM-Stoxx Market 2008 als Besucher?
2. Was bietet mir EM-Stoxx Market 2008 als registrierter Händler?
3. Wie lange läuft EM-Stoxx Market 2008?
4. Wie melde ich mich an?
5. Wie viel kostet die Teilnahme?

Spielbeschreibung

1. Was ist meine Aufgabe?
2. Wie kann ich etwas gewinnen?
3. Was kann ich gewinnen?
4. Was sind die Aktien zum Marktschluss wert?
5. Was zeigt das Ranking?
6. Wie kann ich meinen Depotwert steigern?
7. Wie kommen die Aktien auf den Markt?

Handelsbildschirm

1. Was bedeutet das Datum in der Ordereingabemaske?
2. Was ist der Unterschied zwischen einer CDA und einem Call Market?

Prognosebörsen

1. Was ist eine Prognosebörse?
2. Was ist EM-SToxx Market 2008?

Portfoliohandel

1. Was ist ein Portfolio?
2. Was kostet ein Portfolio?

Figure A.10: EM-Stoxx - Frequently Asked Questions

In Figure A.11, the tutorial page is shown. In the tutorial, the basic functionalities are described following an example. Essential buttons and graphics were highlighted so that the trader could easily identify relevant information.

EM-Stoxx Market 2008

Tutorial

Dieses kurze Tutorial zeigt Ihnen die wichtigsten Funktionen von EM-Stoxx und soll Ihnen den Handel weitestgehend erleichtern!

Anmeldung

Um aktiv an EM-Stoxx teilnehmen und handeln zu können, ist eine Registrierung nötig. Die Teilnahme ist kostenlos. Ein persönlicher Account wird für Sie angelegt, sobald Sie das vollständig ausgefüllte Anmeldeformular abgeschickt haben. Dazu müssen sie unten links auf "Registrieren" klicken.

Nach der Anmeldung erhalten Sie eine Mail mit einem Link und einem einmaligen Aktivierungsscode, der Ihren zuvor gewählten Benutzernamen und ihr Passwort aktiviert. Folgen Sie dem Link und aktivieren Sie dort Ihren Zugang.

Marktauswahl

Direkt nach der Anmeldung bzw. dem Login können Sie den Markt auswählen, in dem Sie handeln wollen. Der Markt zur Europameisterschaft 2008 besteht aus zwei Teilmärkten: einem Markt für die Runde der letzten 16 und einem für die Hauptrunde. Gehandelt werden dort die Aktien der 16 bzw. der letzten 8 beteiligten Nationalmannschaften.

Figure A.11: EM-Stoxx - Tutorial

In Figure A.12 the howto is shown. The howto provided an in depth description of all market functionalities. The essential concept of the market system, the available markets, the endowment, the payout function etc. were described to allow traders to consult the howto once they needed information to proceed trading.

EM-Stoxx Market 2008

Erste Schritte für Einsteiger

Die Idee

EM-Stoxx Market 2008 befasst sich mit der Vorhersage zukünftiger Ereignisse. Die virtuelle Börse fungiert hier als Prognoseinstrument. Die zugrunde liegende Idee wurde im Bereich der Wahlforschung an der University of Iowa erstmalig zur Vorhersage des Ausgangs der US-Präsidentschaftswahl 1988 eingesetzt. Die teilnehmenden Händler von EM-Stoxx Market 2008 können durch den An- und Verkauf von virtuellen Aktien ihre Erwartungen bezüglich des jeweiligen Ereignisses zum Ausdruck bringen. Entscheidend für den Verlauf ist nicht Sympathie, Wohlwollen oder Abneigung, sondern die Erwartungen zu Spielausgängen und Turnierverläufen.

Anmeldung

Zugang zu unserem Handelssystem erhalten Sie über den Login-Bereich links unten auf der Webseite. Um aktiv an EM-Stoxx teilnehmen und handeln zu können, müssen Sie sich registrieren und einen persönlichen Account anlegen. Klicken Sie dazu auf "registrieren". Die Teilnahme an der Börse ist kostenlos. Nach der Anmeldung erhalten Sie eine Mail mit einem Link und einem einmaligen Aktivierungscode, der Ihren zuvor gewählten Benutzernamen und ihr Passwort aktiviert.

Marktauswahl

Direkt nach der Anmeldung können Sie den Markt auswählen, in dem Sie handeln wollen. Es wird insegsamt zwei Märkte geben: Einen für die Vorrunde, in der die Teilnehmer der Finalrunden bestimmt werden und einen für die Hauptrunde mit den verbliebenen 8 Mannschaften. Der Vorrundenmarkt endet mit dem letzten Spiel der Gruppenphase. Im Anschluss werden die Gewinne nach der Auszahlungsregel berechnet und den Händlern gutgeschrieben. Die Aktien der ausgeschiedenen Mannschaften werden mit jeweils 0 EM€ ausbezahlt, aus dem System entfernt und die Aktienwerte der verbliebenen Mannschaften auf ein Ausgangsniveau gesetzt. Im anschließend startenden Markt für die Hauptrunde haben die Spieler aber weiter Zugriff auf ihr Depot.

Anfangsausstattung

Wenn Sie sich für einen Markt anmelden, erhalten Sie eine Anfangsausstattung von 100.000 EM€ sowie 100 Stück aller gehandelten Aktien. Es handelt sich bei EM€ um virtuelle Geldeinheiten, die keinen Gegenwert in realer Währung besitzen.

Figure A.12: EM-Stoxx - HowTo

Table A.1: MAE Group Phase: The MAE for the MM and NMM market can be calculated without distortions and after results were available if teams reached the finals or not. The calculation is based at the point in time once it was determined if a team dropped during the group phase. The error is measured as the difference to the final payout value of 100 or 0 and is reported in percent (%) for each day and for each team.

Market Maker Market (MM)													
Group	Team	07 June	08 June	09 June	10 June	11 June	12 June	13 June	14 June	15 June	16 June	17 June	18 June
A	Portugal	0,38	0,18	0,24	0,17	0,15	0,14	0,00	0,00	0,00	0,00	0,00	0,00
	Turkey	0,58	0,66	0,77	0,82	0,92	0,72	0,71	0,71	0,74	0,00	0,00	0,00
	Czech Republic	0,56	0,60	0,51	0,66	0,58	0,48	0,42	0,42	0,34	0,00	0,00	0,00
	Switzerland	0,44	0,36	0,25	0,20	0,21	0,21	0,00	0,00	0,00	0,00	0,00	0,00
B	Croatia	0,40	0,40	0,31	0,18	0,30	0,43	0,00	0,00	0,00	0,00	0,00	0,00
	Germany	0,10	0,10	0,04	0,09	0,00	0,00	0,06	0,06	0,10	0,10	0,00	0,00
	Austria	0,50	0,23	0,16	0,08	0,09	0,09	0,61	0,61	0,61	0,50	0,00	0,00
	Poland	0,46	0,39	0,26	0,22	0,24	0,28	0,26	0,22	0,12	0,08	0,00	0,00
C	Netherlands	0,96	0,87	0,61	0,19	0,23	0,40	0,20	0,00	0,00	0,00	0,00	0,00
	Italy	0,32	0,15	0,12	0,28	0,26	0,26	0,05	0,05	0,05	0,04	0,49	0,00
	Romania	0,45	0,38	0,25	0,19	0,22	0,22	0,37	0,32	0,19	0,15	0,21	0,00
	France	0,81	0,81	0,81	0,45	0,45	0,71	0,65	0,59	0,44	0,40	0,18	0,00
D	Spain	0,23	0,23	0,02	0,12	0,20	0,31	0,17	0,17	0,00	0,00	0,00	0,00
	Russia	0,55	0,59	0,69	0,66	0,72	0,80	0,81	0,74	0,72	0,65	0,82	0,82
	Sweden	0,46	0,42	0,31	0,39	0,63	0,40	0,37	0,40	0,46	0,64	0,63	0,63
	Greece	0,47	0,42	0,31	0,22	0,14	0,15	0,24	0,20	0,00	0,00	0,00	0,00
Average Error (%)		0,48	0,42	0,35	0,31	0,33	0,35	0,31	0,28	0,24	0,16	0,15	0,09
Non-Market Maker Market (NMM)													
A	Portugal	0,42	0,42	0,42	0,42	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	Turkey	0,44	0,53	0,71	0,80	0,51	0,51	0,51	0,51	0,33	0,00	0,00	0,00
	Czech Republic	0,57	0,57	0,60	0,60	0,55	0,95	0,95	0,95	0,88	0,00	0,00	0,00
	Suisse	0,59	0,29	0,35	0,12	0,09	0,00	0,00	0,00	0,00	0,00	0,00	0,00
B	Croatia		0,25	0,38	0,55	0,20	0,20	0,00	0,00	0,00	0,00	0,00	0,00
	Germany	0,05	0,14	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	Austria	0,42	0,51	0,46	0,42	0,42	0,42	0,01	0,01	0,01	0,05	0,00	0,00
	Poland		0,52	0,39	0,47	0,05	0,05	0,05	0,05	0,05	0,05	0,00	0,00
C	Netherlands	0,40	0,40	0,25	0,20	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	Italy			0,12	0,18	0,13	0,13	0,21	0,21	0,30	0,30	0,35	0,00
	Romania		0,45	0,49	0,49	0,05	0,30	0,26	0,26	0,26	0,26	0,26	0,00
	France			0,86	0,72	0,95	0,95	0,73	0,73	0,40	1,00	1,00	0,00
D	Spain	0,55	0,55	0,14	0,08	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	Russia	0,43	0,45	0,38	0,34	0,90	0,90	0,95	0,95	0,95	0,95	0,95	0,25
	Sweden		0,80	0,65	0,67	0,41	0,95	0,95	0,95	0,96	0,96	0,96	0,95
	Greece	0,40	0,50	0,46	0,30	0,05	0,72	0,72	0,72	0,00	0,00	0,00	0,00
Average Error (%)		0,43	0,45	0,42	0,40	0,27	0,38	0,33	0,33	0,26	0,22	0,22	0,08

B Appendix to Chapter 5

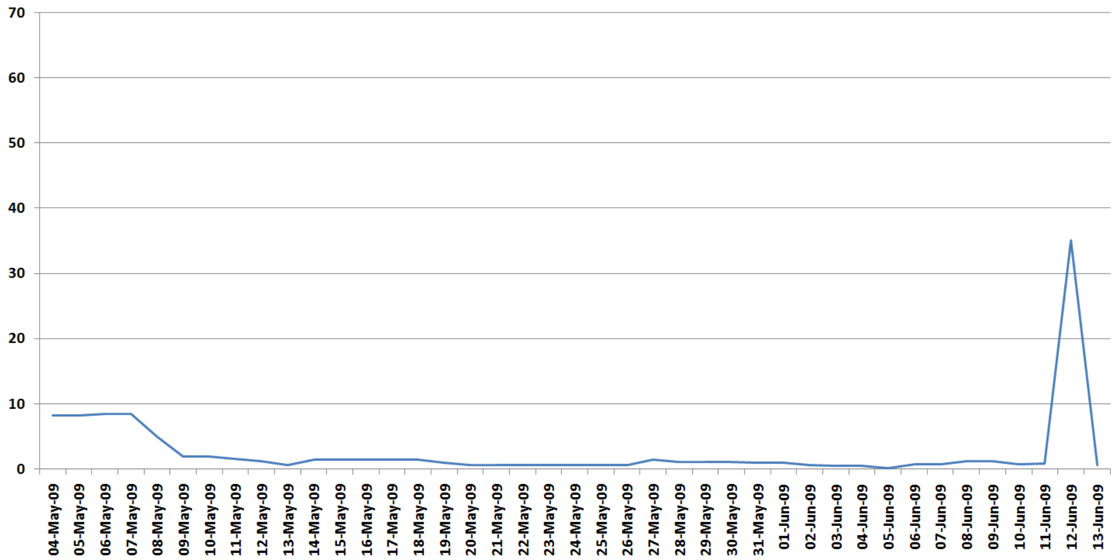


Figure B.1: Price Chart: Twitterinfo

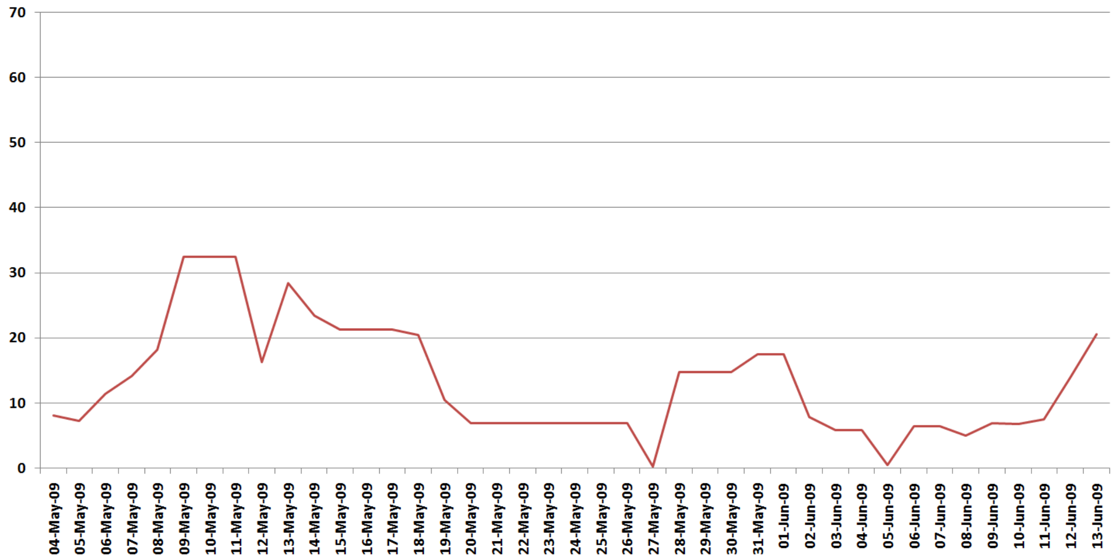


Figure B.2: Price Chart: MEREGIO Platform

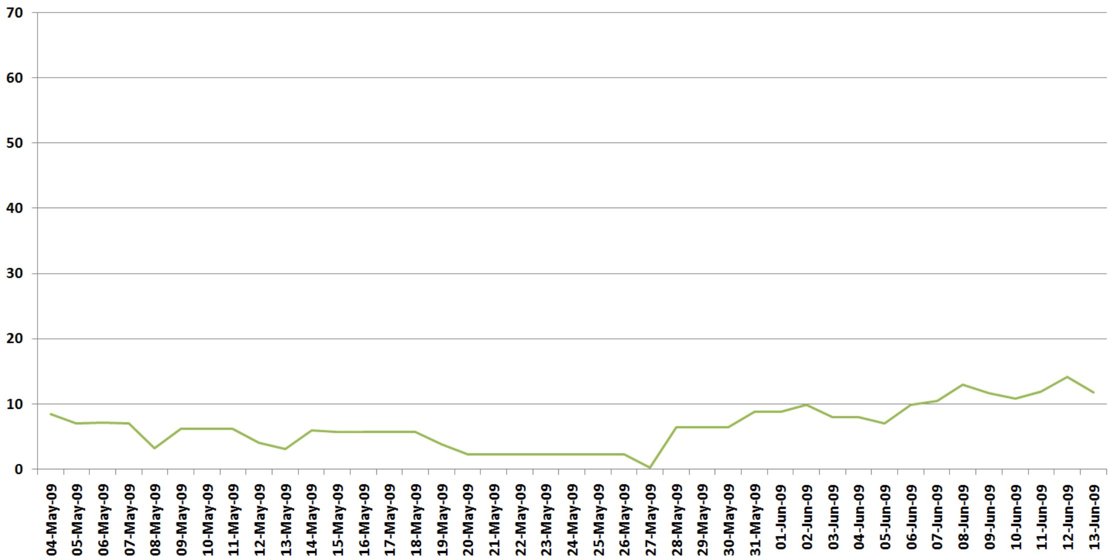


Figure B.3: Price Chart: Home Automation

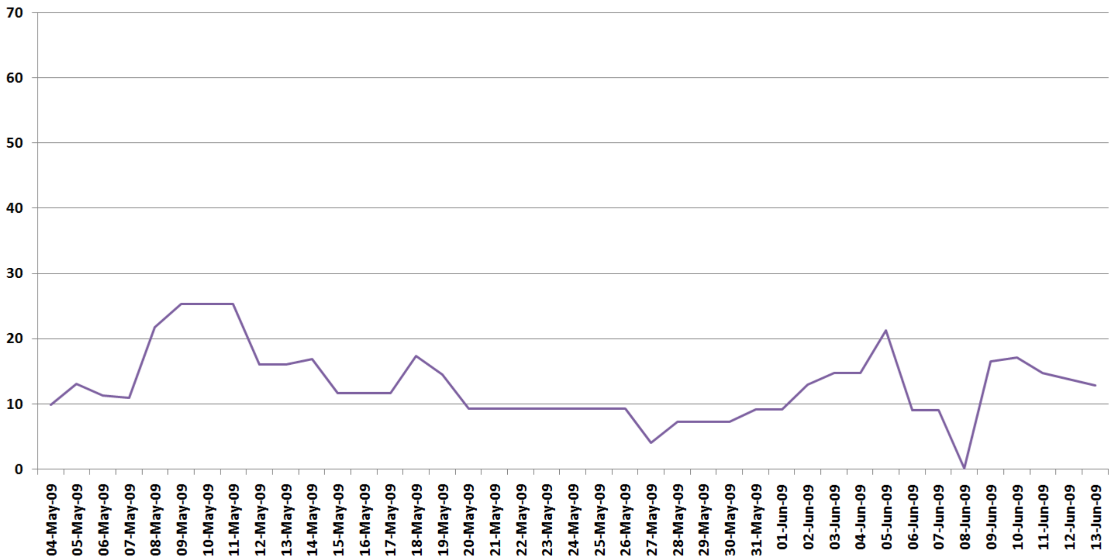


Figure B.4: Price Chart: Parallel Document Processing

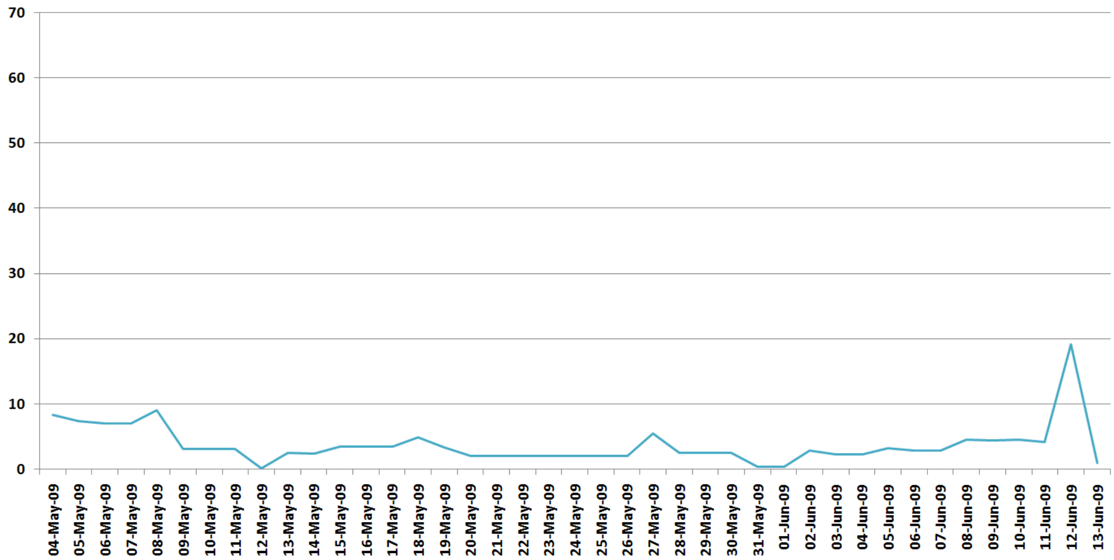


Figure B.5: Price Chart: Intelligent Calendar Management

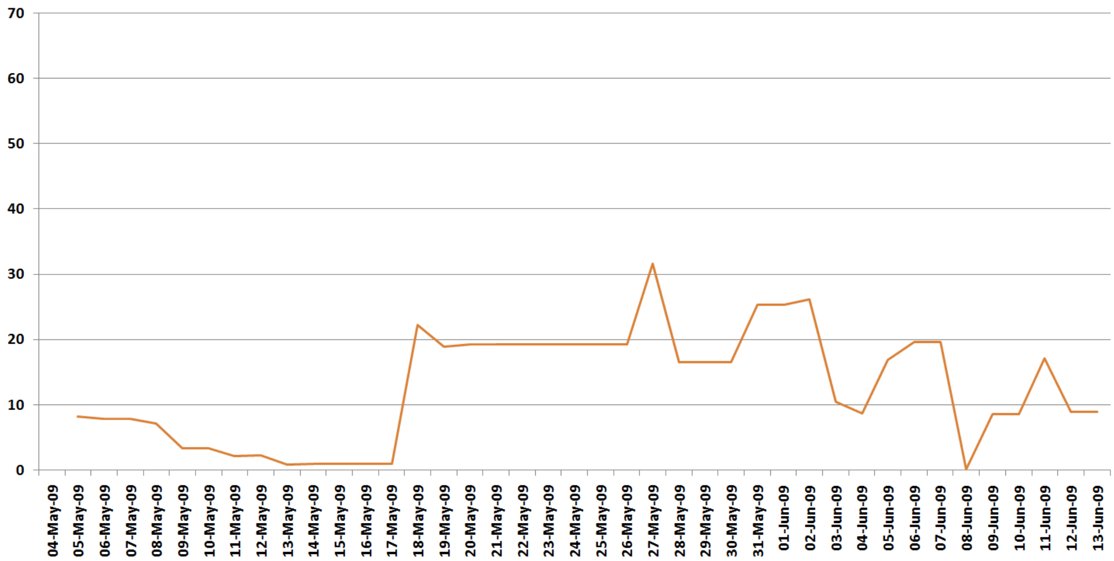


Figure B.6: Price Chart: Web 2.0 Poster

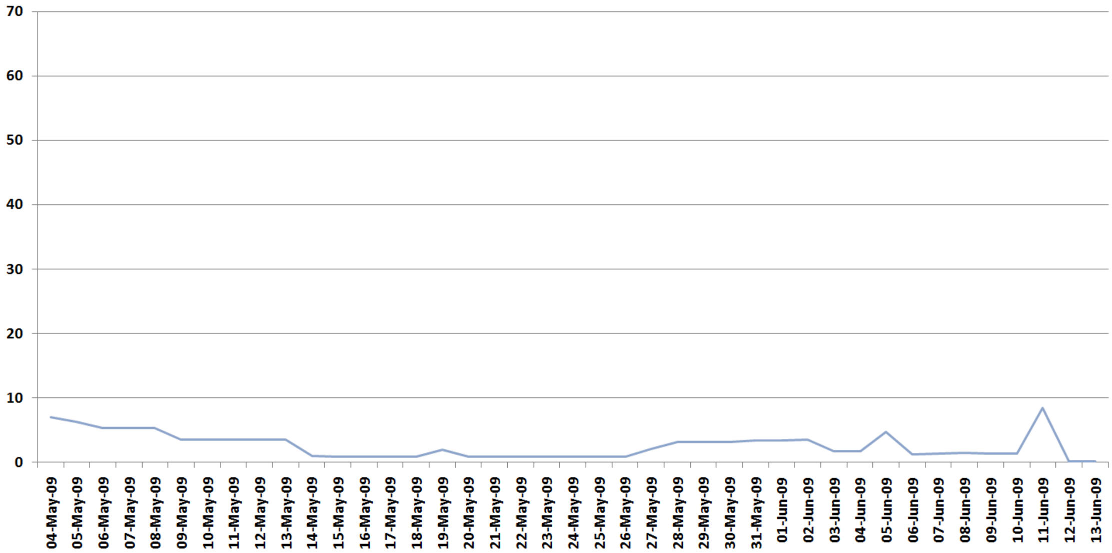


Figure B.7: Price Chart: Digitizing Business Cards

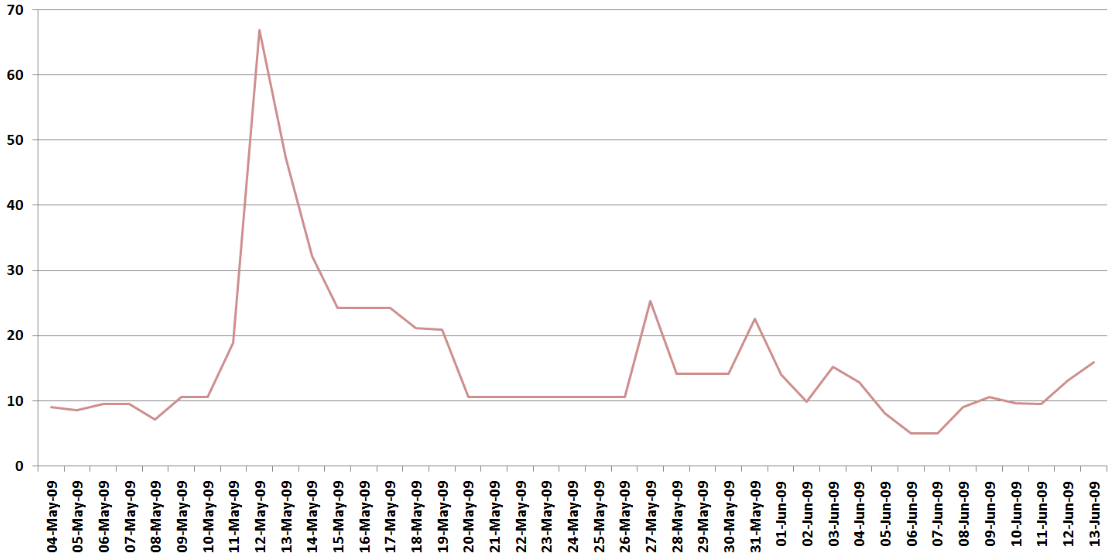


Figure B.8: Price Chart: XingEnBW

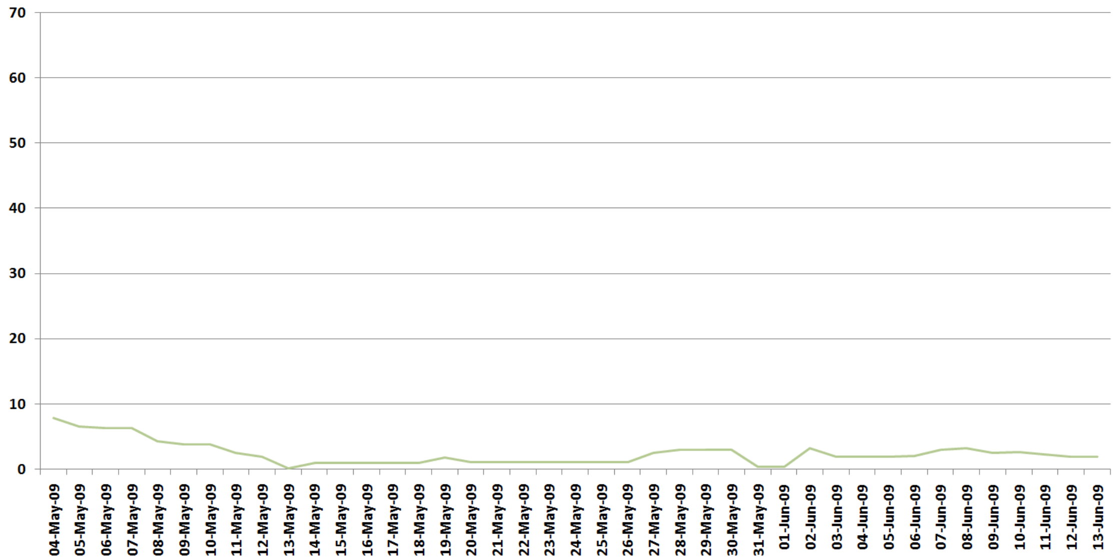


Figure B.9: Price Chart: New Contact Networking

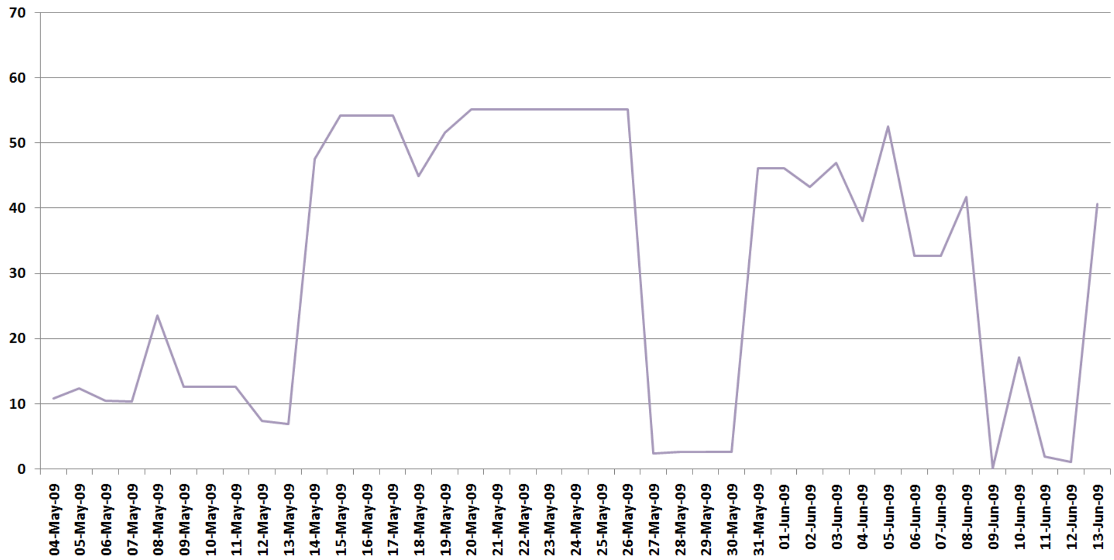


Figure B.10: Price Chart: All in One

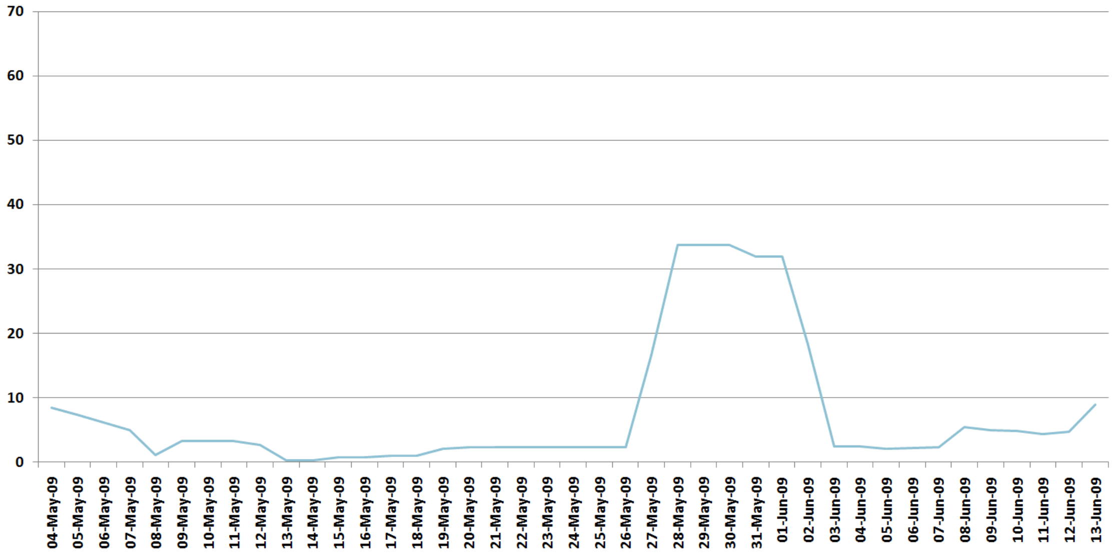


Figure B.11: Price Chart: Hardware Inventory

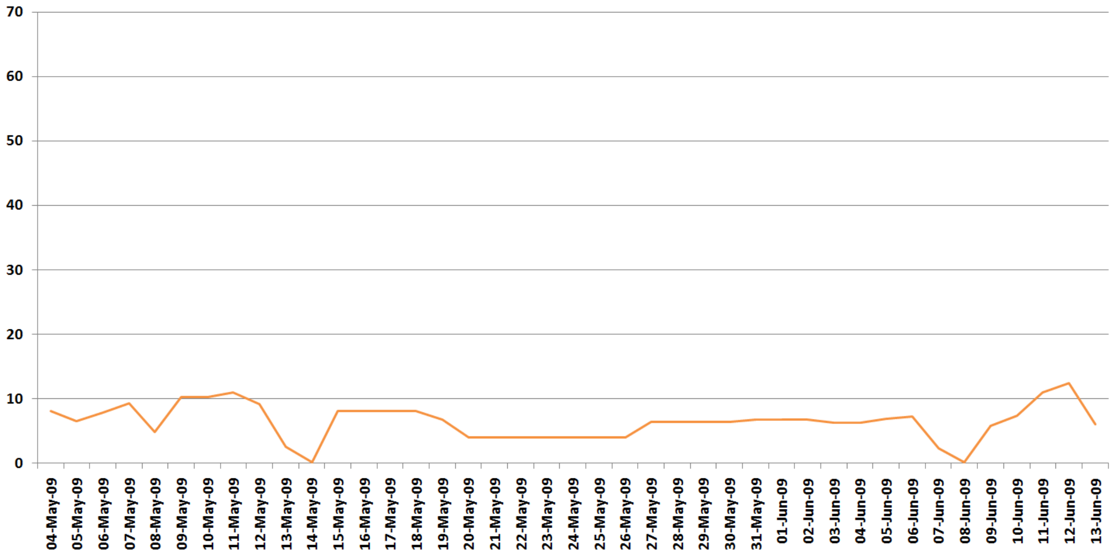
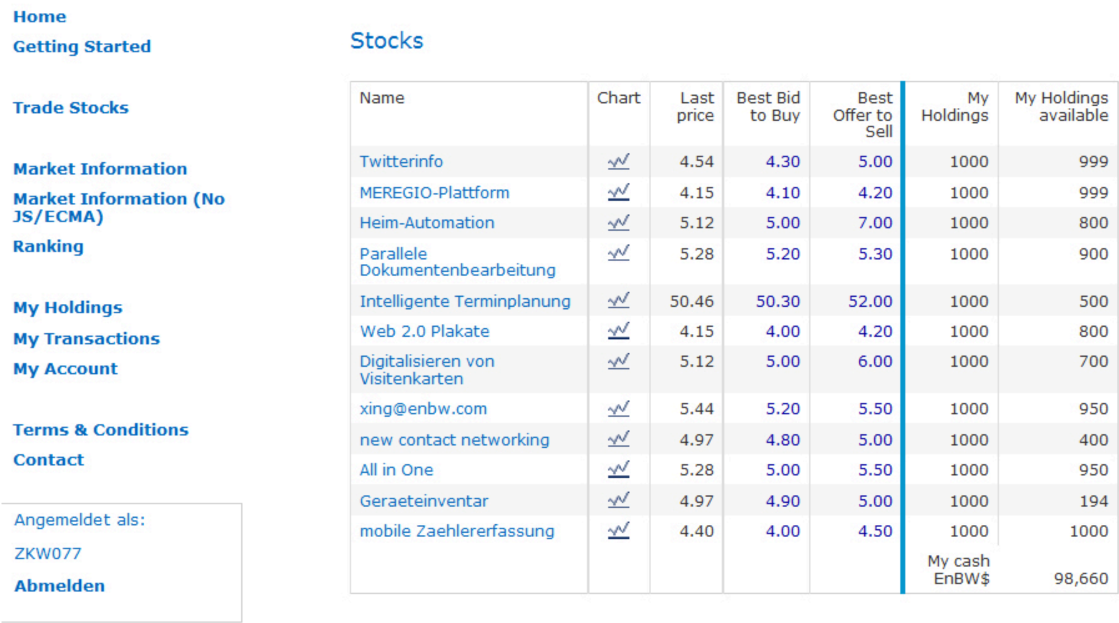


Figure B.12: Price Chart: Mobile Metering

Figure B.13: EnBW - Start Screen

Figure B.13 shows the start screen of the market. On the left hand side, navigation sidebar enables easy access to the basic functionalities. In the middle, a text explaining the objectives of the market is shown. Traders, accessing the market for the first time, are informed about the motivation of the EnBW, why they run the Information Market and what they expect from traders. Furthermore, it is stated that two traders with the best performance will be rewarded with prizes. The benchmark, how the performance of traders is measured, will be explained in Section 5.3.2.



Name	Chart	Last price	Best Bid to Buy	Best Offer to Sell	My Holdings	My Holdings available
Twitterinfo		4.54	4.30	5.00	1000	999
MEREGIO-Plattform		4.15	4.10	4.20	1000	999
Heim-Automation		5.12	5.00	7.00	1000	800
Parallele Dokumentenbearbeitung		5.28	5.20	5.30	1000	900
Intelligente Terminplanung		50.46	50.30	52.00	1000	500
Web 2.0 Plakate		4.15	4.00	4.20	1000	800
Digitalisieren von Visitenkarten		5.12	5.00	6.00	1000	700
xing@enbw.com		5.44	5.20	5.50	1000	950
new contact networking		4.97	4.80	5.00	1000	400
All in One		5.28	5.00	5.50	1000	950
Geraeteinventar		4.97	4.90	5.00	1000	194
mobile Zaehlererfassung		4.40	4.00	4.50	1000	1000
					My cash EnBW$	98,660

Figure B.14: EnBW - Market Overview

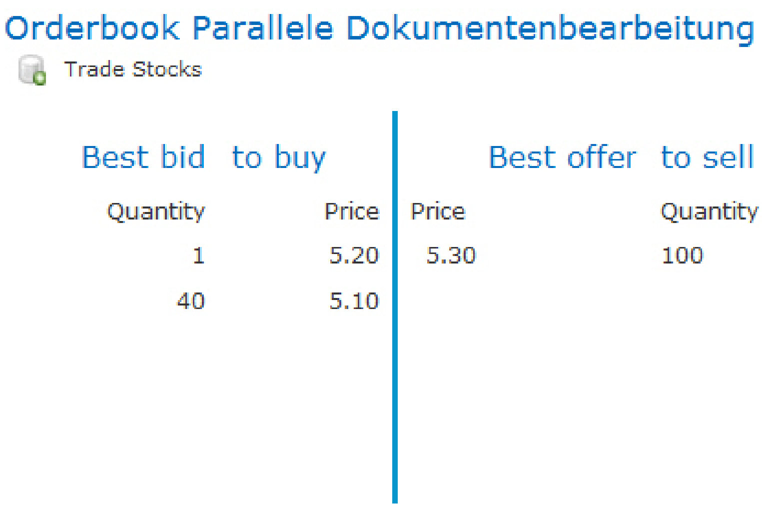


Figure B.15: EnBW - Order Book

By clicking on the button “Trade Stocks”, the market overview displays the current stock prices as well as the best bid and ask offers (cp. Figure B.14[1]). In addition, the depot positions split into “Holdings available” and “Holdings”. The difference is that “Holdings” represent real ownership of stocks whereas “Holdings available” are holdings minus the stocks bounded in open orders in the order book. By clicking a stock in the product list in the stock overview in Figure B.14, the order book pops up which is shown in Figure B.15. On the left hand side, the best buy orders are displayed. On the right side, the best sell orders are displayed.

[1] Cp. Table 5.1 for the translated names of the innovation alternatives.

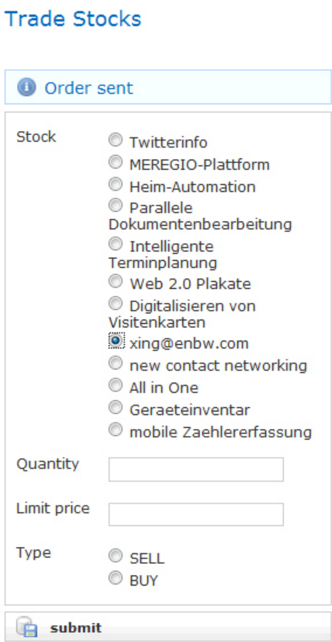


Figure B.16: EnBW - Trading Screen

Orders can be submitted to the system via the trading screen shown in Figure B.16[2]. Via the radio buttons, traders can select the stock they want to trade and enter the number of shares and the limit price. The sell or buy action can be selected via two radio buttons.

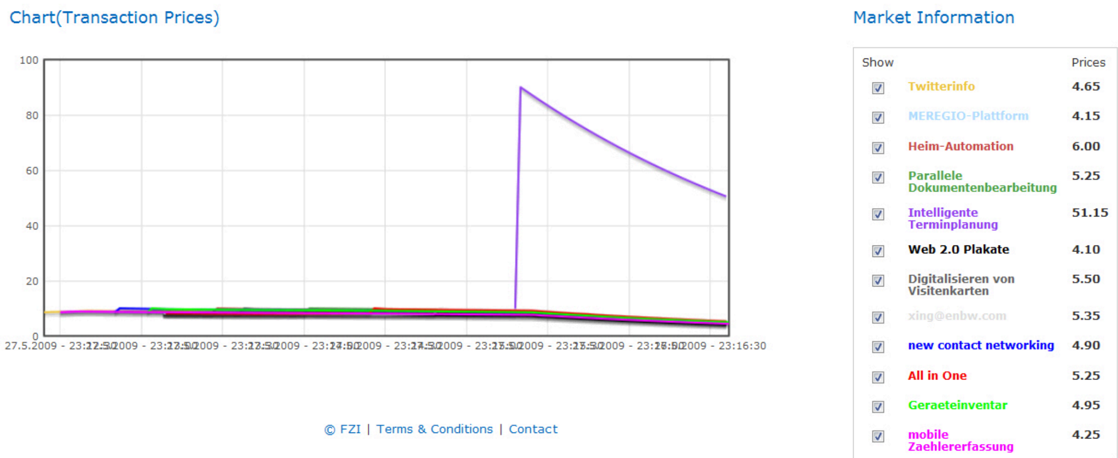


Figure B.17: EnBW - Charts

Via the menu button "Market Information" the price history can be reviewed. In the graph, the historic evolution of stock prices are shown. If the trader wants to see a single stock, he can filter the view via the buttons on the right side (cp. Figure B.17).

[2] Cp. Table 5.1 for the translated names of the innovation alternatives.

My Transactions (show all)

Product	Quantity	Outstanding Quantity	Limit price	Trade price	Type	Status	Cancel	Date
Parallele Dokumentenbearbeitung	40	40	5.10	5.10	buy	open	Delete	09:50 17-03-2010
mobile Zaehlererfassung	90	90	4.50	4.50	sell	open	Delete	09:47 17-03-2010
mobile Zaehlererfassung	9	9	4.00	4.00	buy	open	Delete	09:47 17-03-2010
Geraeteinventar	806	806	5.00	5.00	sell	open	Delete	09:47 17-03-2010
Geraeteinventar	44	44	4.90	4.90	buy	open	Delete	09:46 17-03-2010
All in One	50	50	5.50	5.50	sell	open	Delete	09:46 17-03-2010
All in One	5	5	5.00	5.00	buy	open	Delete	09:46 17-03-2010
new contact networking	600	600	5.00	5.00	sell	open	Delete	09:45 17-03-2010
new contact networking	6	6	4.80	4.80	buy	open	Delete	09:45 17-03-2010
xing@enbw.com	50	50	5.50	5.50	sell	open	Delete	09:44 17-03-2010
xing@enbw.com	66	66	5.20	5.20	buy	open	Delete	09:44 17-03-2010
Digitalisieren von Visitenkarten	300	300	6.00	6.00	sell	open	Delete	09:43 17-03-2010
Digitalisieren von Visitenkarten	7	7	5.00	5.00	buy	open	Delete	09:43 17-03-2010
Web 2.0 Plakate	200	200	4.20	4.20	sell	open	Delete	09:43 17-03-2010

Figure B.18: EnBW - Transactions

After submitting an order, it can either lead to a direct transaction, if a matching order is already in the order book or it stays in the order book until a matching order comes in. In Figure B.18[3], all transactions can be reviewed whereas open orders can be deleted.

Ranking**

Rank	User Name	Value	Winning Probability*
1	ZKW100	206,100.10	100 %
2	ZKW001	203,880.00	1.00 %
3	ZKW002	203,880.00	1.00 %
4	ZKW003	203,880.00	1.00 %
5	ZKW004	203,880.00	1.00 %
6	ZKW005	203,880.00	1.00 %
7	ZKW006	203,880.00	1.00 %
8	ZKW007	203,880.00	1.00 %
9	ZKW008	203,880.00	1.00 %
10	ZKW009	203,880.00	1.00 %
11	ZKW010	203,880.00	1.00 %
12	ZKW011	203,880.00	1.00 %
13	ZKW012	203,880.00	1.00 %
14	ZKW013	203,880.00	1.00 %
15	ZKW014	203,880.00	1.00 %
16	ZKW015	203,880.00	1.00 %
17	ZKW016	203,880.00	1.00 %
18	ZKW017	203,880.00	1.00 %
19	ZKW018	203,880.00	1.00 %
20	ZKW019	203,880.00	1.00 %
21	ZKW020	203,880.00	1.00 %
22	ZKW021	203,880.00	1.00 %

Figure B.19: EnBW - Ranking

Stocks were paid out after the market close. Hence, traders get a monetary payments depending of how many stocks they have in their portfolio. After the payout of shares, the money they get affects their total portfolio value. As an incentive and competitive element, all traders are listed in a ranking-based on their portfolio value. An example ranking is shown in Figure B.19.

[3] Cp. Table 5.1 for the translated names of the innovation alternatives.

Table B.1: Market Statistics - weekwise min/max: The minimum and maximum prices are shown for each contract and each week.

ID	Name	min_1	min_2	min_3	min_4	min_5	min_6	max_1	max_2	max_3	max_4	max_5	max_6
01	Twitterinfo	2,50	0,27	0,68	0,64	0,19	0,64	9,00	2,00	1,43	2,00	1,00	90,00
02	MEREGIO Platform	6,26	8,99	5,64	0,10	0,10	0,28	50,00	35,00	29,00	29,00	12,00	17,40
03	Home Automation	0,89	3,10	2,64	0,10	5,16	7,17	8,80	6,00	2,64	30,00	14,45	25,00
04	Parallel Document Processing	8,34	8,50	10,87	1,95	6,59	0,10	40,00	20,00	20,00	20,00	39,50	21,00
05	Intelligent Calendar Management	3,80	0,14	2,34	0,50	0,17	1,80	20,00	8,15	2,34	2,34	2,34	5,50
06	Web 2.0 Poster	4,00	0,24	10,01	14,21	4,16	0,10	10,00	5,15	30,00	43,32	40,00	27,95
07	Digitizing Business Cards	4,00	0,75	1,00	1,00	1,24	0,10	7,05	1,00	2,50	5,00	7,40	9,23
08	xing@enbw.com	2,95	16,64	12,83	12,90	4,13	3,86	19,99	100,00	33,00	33,00	33,00	24,00
09	New Contact Networking	5,00	0,27	1,28	0,50	1,30	1,94	8,34	2,50	2,50	6,88	5,90	4,50
10	All in one	9,00	7,00	23,33	1,02	21,63	0,10	50,00	77,00	72,00	10,00	72,00	45,00
11	Hardware Inventory	0,19	0,27	1,47	3,00	0,94	4,10	9,00	3,80	3,00	48,50	48,50	6,99
12	Mobile Metering	5,87	0,25	4,80	3,86	4,07	0,10	12,00	11,67	9,95	10,50	10,50	18,54

Table B.2: Market Statistics - weekwise median/average: The median as well as average prices are shown for each contract and each week.

ID	Name	med_1	med_2	med_3	med_4	med_5	med_6	$\varnothing_1$	$\varnothing_2$	$\varnothing_3$	$\varnothing_4$	$\varnothing_5$	$\varnothing_6$
01	Twitterinfo	8,34	2,00	1,43	1,50	1,00	0,99	8,07	1,36	1,18	1,51	0,56	41,49
02	MEREGIO Platform	8,35	20,00	29,00	0,10	12,00	6,00	14,86	24,56	13,87	13,78	6,14	7,81
03	Home Automation	8,80	5,00	2,64	0,10	14,45	11,40	5,86	4,52	2,64	18,08	8,06	13,10
04	Parallel Document Processing	10,00	20,00	15,00	5,00	20,00	0,10	14,04	15,81	14,05	5,42	21,13	6,56
05	Intelligent Calendar Management	9,00	2,00	2,34	2,34	0,17	2,34	7,25	0,30	2,34	2,24	1,39	3,38
06	Web 2.0 Poster	8,34	2,10	30,00	24,00	40,00	6,86	7,53	2,09	17,86	27,33	19,93	5,49
07	Digitizing Business Cards	7,05	1,00	2,50	1,00	5,00	1,55	5,63	0,92	1,62	2,25	5,81	3,16
08	xing@enbw.com	9,50	19,99	33,00	33,00	14,06	24,00	9,91	37,43	18,98	26,30	7,13	10,19
09	New Contact Networking	8,34	2,50	2,50	0,50	5,90	3,30	6,66	1,53	1,62	2,94	2,74	2,96
10	All in one	9,00	9,00	72,00	10,00	72,00	45,00	12,95	22,40	53,34	3,10	50,85	3,05
11	Hardware Inventory	9,00	3,80	3,00	3,00	48,50	4,10	2,71	1,23	2,11	14,09	5,09	5,51
12	Mobile Metering	8,50	11,00	9,95	5,00	10,50	2,39	7,49	8,49	6,92	6,23	6,51	4,09

Fragebogen – Innovationsbewertung

1. Welche Tätigkeit/Aufgabe begleiten Sie in der EnBW? (Mehrfachnennung möglich)

☐	Personalverantwortung
☐	Geschäftsverantwortung/Ergebnisverantwortung (Leitung eines Geschäftsbereichs)
☐	Mitarbeiter
☐	Mitarbeiter, der mit 50% oder mehr seiner Tätigkeit mit innovationsrelevanten Themen beschäftigt ist
☐	Sonstiges:

2. Welche Vorschläge des heutigen Tages erachten Sie als besonders aussichtsreich, um in einer Projektidee verwirklicht zu werden? **Wählen Sie bitte bis zu drei Ideen aus.**

Fire Eagle	Pachube	Google Latitude	Barcoo: Mit Barcode-Scan nutzergenerierte Daten abfragen	Xsights
☐	☐	☐	☐	☐
Mobiler Ratschlagsservice	Web 3.0	Geographic Peformance Report	Microblogging als Marketingool	Soliocharger: Solarakku speichert Energie bis zu einem Jahr
☐	☐	☐	☐	☐
Tiki Tag	Piezo Konverter	Heim Automation	Digsby: All-In-One Lösung für Echtzeitkommunikation im Internet	Web 2.0 Funktionalitäten im Projektmanagement
☐	☐	☐	☐	☐
Evernote: Gleichzeitige Veröffentlichung von Informationen	Google Power Meter			
☐	☐			

1

Figure B.20: EnBW - Questionnaire 1/6

3. Wie beurteilen Sie den Ansatz, Informationsmärkte zur Bewertung von Innovationen zu nutzen?

sehr gut	gut	neutral	weniger gut	nicht gut
☐	☐	☐	☐	☐

4. Wie hoch schätzen Sie Ihren persönlichen Aufwand, diese Methode als Bewertungstool in der EnBW zu nutzen?

sehr aufwändig	aufwändig	neutral	weniger aufwändig	nicht aufwändig
☐	☐	☐	☐	☐

5. Wie hoch schätzen Sie Ihre Motivation, einen Informationsmarkt über einen längeren Zeitraum zu nutzen?

sehr hoch	hoch	neutral	niedrig	sehr niedrig
☐	☐	☐	☐	☐

6. Denken Sie, dass die EnBW mit Informationsmärkten Innnovationen besser bewerten kann/können wird?

sehr gut	gut	neutral	weniger gut	nicht gut
☐	☐	☐	☐	☐

7. Welche Probleme sehen Sie in der Verwendung von Informationsmärkten? (Mehrfachnennung möglich)

☐	Ich habe keine Zeit, mich über einen längeren Zeitraum mit Informationsmärkten zu beschäftigen
☐	Bedienung des Tools ist mir unklar/finde ich unintuitiv
☐	Ich weiß nicht, nach welcher Strategie ich handeln soll
☐	Ich habe Probleme, den Nutzen/Realisierungsaufwand der Idee einzuschätzen und kann daher keine Informationen im Tool abbilden
☐	Sonstiges:

2

Figure B.21: EnBW - Questionnaire 2/6

8. a) Was schränkt Sie z.Zt. in ihrer „Innovationstätigkeit“ ein? (Mehrfachnennung möglich)

☐	Keinen persönlichen Anreiz, Ideen abzugeben und zu verfolgen
☐	Kein Geld zur Ausarbeitung von Konzepten/Prototypen vorhanden
☐	Keine Zeit, um mich mit Innovationen zu beschäftigen
☐	Keine Austauschmöglichkeiten unter Kollegen/Vorgesetzen
☐	Kein Vorschlagssystem vorhanden
☐	Sonstiges:

8. b) Was wünschen Sie sich zusätzlich, um dies zu verbessern und Sie in ihrer „Innovationstätigkeit“ zu unterstützen?

9. Gibt es einen formalisierten Innovationsprozess in Ihrem Unternehmen/Gesellschaft, der von der Ideenfindung bis zur Markteinführung durchlaufen wird?

☐	Ja, es gibt einen formalisierten Innovationsprozess für Dienstleistungen, der schriftlich fixiert ist
☐	Ja, es gibt einen formalisierten Innovationsprozess für Dienstleistungen, der aber nicht schriftlich fixiert ist
☐	Nein, es gibt keinen Innovationsprozess für Dienstleistungen
☐	Keine Angabe möglich

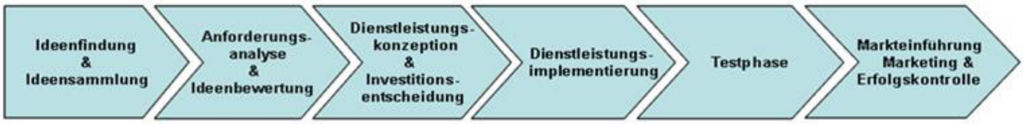
10. Besitzen alle Mitarbeiter Ihres Unternehmens/Gesellschaft Freiräume während der Arbeitszeit, neue Innovationen zu entwickeln?

☐	Ja, hierbei handelt es sich um eine offizielle Regelung des Unternehmens
☐	Ja, es wird gerne gesehen, ist aber nicht formal dokumentiert
☐	Nein, es wird nicht gerne gesehen
☐	Nein, es kommt praktisch nicht vor
☐	Keine Aussage möglich

3

Figure B.22: EnBW - Questionnaire 3/6

11. Angenommen, folgender Prozess würde in Ihrem Unternehmen/Gesellschaft „gelebt" - Wie sehr wären Kunden (interne Kunden als auch Endkunden) in den einzelnen Phasen integriert?



Phase	gar nicht	gering	mittel	stark	keine Angabe möglich
Ideenfindung und Ideensammlung	☐	☐	☐	☐	☐
Anforderungsanalyse und Ideenbewertung	☐	☐	☐	☐	☐
Dienstleistungskonzeption und Investitionsentscheidung	☐	☐	☐	☐	☐
Dienstleistungsimplementierung	☐	☐	☐	☐	☐
Testphase	☐	☐	☐	☐	☐
Markteinführung, Marketing und Erfolgskontrolle	☐	☐	☐	☐	☐

12. Welche der folgenden Tools verwenden Sie innerhalb des Innovationsprozesses von Dienstleistungen?

Tool zur Ermittlung von Ideen	Tool für die Ideenbewertung	Tool für die Kollaboration	Tool für die Projektsteuerung	Tool für die Prozess-modellierung
☐	☐	☐	☐	☐
Tools zur Kommunikation	Es werden keine Tools verwendet	Keine Angaben Möglich	Sonstiges:	
☐	☐	☐		

13. Welche der folgenden Konzepte und Möglichkeiten werden in Ihrem Unternehmen genutzt, um Qualität und Potential von Dienstleistungen zu beurteilen?

Kunden-beobachtung	Kunden-befragung	Beschwerden-management	Kundenforen/ User Foren	Kundenworkshops
☐	☐	☐	☐	☐
Expertenpanels	Lead User Konzept	Keine dieser Konzepte und Möglichkeiten werden genutzt	Keine Angabe möglich	Sonstiges:
☐	☐	☐	☐	

4

Figure B.23: EnBW - Questionnaire 4/6

14. Welche der folgenden Methoden verwenden Sie, um neue Dienstleistungsideen zu bewerten?

Checklisten	Pro- und Contra-Methode	SWOT-Analyse	Nutzwert-Analyse
☐	☐	☐	☐
Kundennutzen-Matrix	Investitionsrechnung	Kosten-Nutzen-Analyse	Keine dieser Methoden wird verwendet
☐	☐	☐	☐
Portfolio-Methoden	Keine Angabe möglich	Sonstiges:	
☐	☐	☐	

15. Beurteilen Sie bitte den Grad der Eigeninitiative der Mitarbeiter Ihres Unternehmens/Gesellschaft, an der Dienstleistungsinnovation mitzuwirken.

Stufe 1: Mitarbeiter werden nicht aktiv bis ihr Vorgesetzter dies einfordert
Stufe 2: Mitarbeiter fragen ihren Vorgesetzen aktiv nach Möglichkeiten, sich zu beteiligen
Stufe 3: Mitarbeiter empfehlen von sich aus dem Vorgesetzen sinnvolle Aktivitäten und führen diese nach Vereinbarung selbstständig durch
Stufe 4: Mitarbeiter unternimmt eigenverantwortlich Aktivitäten und führen diese nach Vereinbarung selbstständig durch
Stufe 5: Mitarbeiter unternimmt selbstständig Aktivitäten und berichten darüber in längeren Abständen regelmäßig

	Stufe 1	Stufe 2	Stufe 3	Stufe 4	Stufe 5
Wie hoch ist der Grad an Eigeninitiative der Mitarbeiter ihres Unternehmens?	☐	☐	☐	☐	☐
Welcher Grad wird von ihrem Unternehmen gefördert?	☐	☐	☐	☐	☐
Wie wäre Ihrer Meinung nach der Idealzustand?	☐	☐	☐	☐	☐

5

Figure B.24: EnBW - Questionnaire 5/6

16. Für wie geeignet halten Sie folgende Formen der Mitarbeitermotivation?

	nicht geeignet	weniger geeignet	mäßig geeignet	gut geeignet	sehr gut geeignet	keine Einschätzung möglich
Anerkennung in Form von Auszeichnungen durch die Geschäfts- oder Bereichsleitung	☐	☐	☐	☐	☐	☐
Belohnung in Form von Prämien	☐	☐	☐	☐	☐	☐
Erfolgsbeteiligung an der jeweiligen Dienstleistungsinnovation	☐	☐	☐	☐	☐	☐
Dienstleistungsinnovation als Teil der Zielvereinbarung	☐	☐	☐	☐	☐	☐
Teilnahme an externen Veranstaltungen oder Konferenzen	☐	☐	☐	☐	☐	☐
Sonstiges:	☐	☐	☐	☐	☐	☐

Vielen Dank!

Kontakt:

6

Figure B.25: EnBW - Questionnaire 6/6

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