František Kopřiva

Essays on the Behavior of Agents in Financial Markets

Dissertation

Prague, July 2012

CERGE

Center for Economic Research and Graduate Education
Charles University Prague

Essays on the Behavior of Agents in Financial Markets

František Kopřiva

Dissertation

Prague, July 2012

Dissertation Committee

JAN HANOUSEK (CERGE-EI; chair)
RANDALL K. FILER (Hunter College, City University of New York)
EVŽEN KOČENDA (CERGE-EI)

Referees

GEORGE VACHADZE (College of Staten Island, City University of New York)
IFTEKHAR HASAN (Fordham University; Bank of Finland)

Acknowledgments

Looking back, I am very grateful for all I have received throughout my PhD studies of economics at CERGE-EI. First of all, I would like to express my deepest gratitude to my supervisor Jan Hanousek. He provided me several invaluable nudges: First, as an advisor of my master's thesis during my studies of statistics he encouraged me to pursue a PhD in Economics. Second, he pushed me to undertake mobilities abroad. He has also provided me with priceless comments, insights and motivation.

I would also like to thank Eva Hromádková for her unceasing support, help with formation of my ideas, and invaluable help with editing. Without her faith in me I would not be able to accomplish this task.

I am deeply thankful to all the other people and friends who were ready to consult with me on my ideas, helped me with their comments, and gave me critique and feedback on my work. To mention just some of them, I would like to thank Avner Shaked, Randall Filer, Filip Matějka, Mário Vozár, Štěpán Jurajda, Barbara Pertold-Gebická, Filip Pertold, Katarína Kálovcová, Natalia Shestakova, Jan Kmenta, Peter Katusčák, Levent Çelik, Andreas Ortmann and Jan Večeř.

I would like to thank my parents and my family for always believing in me and supporting me in everything I pursue.

All the people I've met and experiences I have had shaped me as a person and led me to where I am now – more confident, more open-minded, and definitely more humble. I believe that one should always try to give more than one gets. I hope that I will be at least partly as helpful to the people around me as they have been helpful to me.

Prague, Czech Republic
July, 2012 František

Table of Contents

Abstract

In the first chapter, I focus on the extent of information-driven trading originating from order flows to capture the behavior of the market makers on an emerging market. With my supervisor, we modified the classical Easley et al. (1996) model for the probability of informed trading using a jackknife approach in which trades of one particular market maker at a time are left out from the sum of all buys and sells. Using the estimates from the jackknife approach, for each market maker we test whether the order flows associated with the particular market maker behaved significantly different from the others. Data from the Prague Stock Exchange SPAD trading platform are used to demonstrate our methodology. Finding significant differences in the probability of informed trading computed from order flows, we conclude that order flows could reveal the extent of information-driven trading and could potentially be used by regulatory authorities to identify the suspicious behavior of market participants.

In the second chapter I analyze the potential conflict of interest between associated analysts and brokers. In contrast to the existing literature, with my supervisor, we do not analyze prediction accuracy and/or biases in analyst recommendations. Instead we focus our analysis on brokers and examine whether their behavior systematically differs before and after investment recommendations are released. The evolution and dynamics of brokers' quotes and trades are used to test for systematic trading patterns around the release of one’s own investment recommendation. In the model we control for brokers' responses to other investment advice and employ a SUR estimation framework. Data from the Prague Stock Exchange are used to demonstrate our methodology. Finding significant and systematic differences in brokers' behavior, we conclude that misuse of investment recommendations is widespread.

In the third chapter, I analyze the risk preferences of bettors using data from the world largest betting exchange Betfair. The assumption of a constant bet size, commonly used in the current literature, leads to an unrealistic model of bettor's decision making as a choice between high return - low variance and low return - high variance bet, automatically implying risk loving preferences of bettor. However, the data show that bettors bet different amounts on different odds. Thus, simply by introducing the computed average bet size at given odds I transform bettor's decision problem into a standard choice between low return - low variance and high return - high variance bets, and I am able to correctly estimate the risk attitudes of bettors. Results indicate that bettors on Betfair are either risk neutral (tennis and soccer markets) or slightly risk loving (horse races market). I further use the information about the average bet size to test the validity of EUT theory. The results suggest that, when facing a number of outcomes with different winning probabilities, bettors tend to overweight small and underweight large differences in probabilities, which is in direct contradiction to the linear probability weighting function implied by EUT.

Abstrakt

V první části své dizertační práce se zaměřuji na odhad rozsahu obchodování na základě neveřejných informací pramenící ze způsobu chování tvůrců trhu na malém rozvíjejícím se kapitálovém trhu. Vzhledem k vysokému procentu blokových obchodů v letech 2003-05 mohli tvůrci trhu zaměřující se na velké investory získat významný zdroj neveřejných informací. Rozšířením modelu Easley et al. (1996) jsme (společně s mým supervisorem) navrhli metodologii, která umožňuje analyzovat specifické chovaní market makerů na českém kapitálovém trhu a vliv tohoto chování na obchodování na základě neveřejných informací. Vzhledem k výrazným rozdílům v chování jednotlivých market makerů naše výsledky, nikoliv překvapivě, naznačují, že čeští tvůrci trhu mají významný vliv na rozsah obchodování na základě neveřejných informací. Z našich výsledků dále vyplývá, že za současného regulatorního rámce jsou tvůrci trhu schopni obchodovat na základě určité informace po překvapivě dlouhé časové období. Tato studie by mohla přispět ke zlepšení detekčních mechanismů regulatorních orgánů v ČR, jelikož naše metodologie umožňuje detekci nestandartního chování jednotlivých tvůrců trhu.

Druhá část dizertační práce analyzuje potencionální konflikt zájmů, který může vznikat mezi analytiky a obchodníky s cennými papíry. Na rozdíl od existující literatury neanalyzujeme (opět společně s mým supervisorem) kvalitu investičních doporučení, ale zaměřujeme se na chování obchodníků s cennými papíry a zkoumáme, zda se jejich chování liší před a po uveřejnění investičních doporučeních. Pro testování systematických obchodních praktik okolo uveřejnění investičních doporučení od analytiků pracujících pro určitého obchodníka s cennými papíry používáme vývoj a dynamiku kotací a obchodů tohoto obchodníka. Za použití SUR regresní analýzy naše metodika zachycuje i vzájemnou interakci chování různých obchodníků i analytiků. Pro demonstraci naší metodiky používáme data z Burzy cenných papírů v Praze. Naše výsledky naznačují na překvapivě výrazné odlišnosti v systematickém chování obchodníků v okolí zveřejnění investičních doporučení v ČR.

V třetí části dizertační práce se zabývám analýzou chování sázejících na největší online burze sázek – Betfair. Cílem této analýzy je bližší pochopení jednoho ze základních kamenů ekonomické teorie – rozhodování lidí v podmínkách nejistoty a jejich přístup k riziku. Sázení je jednou z mála situací v reálném životě, které se pro ověřování různých teorií o chování lidí v rámci rizika a nejistoty přímo vybízí. Všechny dosavadní studie na toto téma však opomíjely jeden podstatný fakt v rozhodování sázkařů - při výběru sázky hraje významnou roli nejen daný kurz, ale také výše sázky. Využitím dat z online burzy sázek nejen o výsledných kurzech na danou sázkovou příležitost ale i o, z dat vypočtených průměrně, vsazených částkách, tato studie velmi významně přispívá k analýze chování v rámci rizika a nejisoty. Studie, za použití nově navržené metodologie, testuje platnost jednoho z hlavních předpokladů EUT o racionálním přístupu k pravděpodobnostem. Moje výsledky naznačují, že sázkaři dávají při rozhodování v rámci rizika malým rozdílům v pravděpodobnostech blízko 0% vyšší váhu než čistě racionálně smýšlející člověk a naopak velkým rozdílům v pravděpodobnostech výrazně nižší váhu než čistě racionálně smýšlející člověk.

General Introduction

"We are drowning in information, while starving for wisdom. The world henceforth will be run by synthesizers, people able to put together the right information at the right time, think critically about it, and make important choices wisely."
Edward Osborne Wilson

Financial markets are the heart of every modern economy. As the source of income for a significant number of people, they have always attracted the interest of corporate and individual investors, as well as academic researchers. Most of these analysts aim to understand why prices are set at a given level and what the determinants behind their evolution are over time. Therefore, they focus primarily on analyzing price time series and their characteristics. Nevertheless, even though prices represent the outcome of market forces and as such carry general information about market participants, they do not provide full information on individuals' behavior.

However, with increasing availability and richness of data we are able to answer more and more questions about the motivations and decisions of various (important) subgroups of market participants. The issue is no longer the lack of data, but inadequate methods to extract and summarize relevant information in a systematic way. In this dissertation, I design several new methods of data analysis and apply them to large publicly available datasets to demonstrate how one can use the existing data to understand the behavior of various market participants, and to identify potentially deleterious behavioral patterns. Specifically, I focus on two issues: whether and how market participants exploit a privileged position on the market stemming from their market power (chapter 1) or access to information (chapter 2); and what we can learn about decision making under risk and uncertainty and about the behavioral misperceptions of participants in financial markets (chapter 3).

In the first chapter I analyze the role of market makers in information-driven trading on an emerging market. I focus on differences in the information content of trades of particular market makers on the Prague Stock Exchange (PSE) in the Czech Republic. PSE is a small emerging market and thus every large order could significantly affect the price on the market. Yet, the market microstructure allows large investors to negotiate the price for large block trades with the market makers. Such a practice may lead to a situation in which one or several of the market makers are informed and thus have an advantage over the rest of the market.

Due to the high share of block trades on the total volume traded in the years 2003-05, market makers focused on large customers may have a significant source of private information on the PSE. We extend Easley et al.'s (1996) model and use the intra-day data from the Prague Stock Exchange to identify suspicious trading behavior of particular Czech market makers. If some market makers possess private information about a large block order, they would behave differently than the remaining market makers. We test the hypothesis by comparing the sum of buys and sells for a given market maker with the overall sum of buys and sells; significant differences in the positions of market makers lead us to conclude that the market makers affect the extent of information-driven trading.

Under current regulation market makers are able to protect their private information for a surprisingly long period of time. Although participants on the market may be aware that other market makers possess private information about the value of an asset, they are not able to prove it. Our study should, therefore, contribute to the development of detection mechanisms used by regulatory authorities on emerging markets in identifying the suspicious behavior of particular market participants.

In the second chapter I focus on the conflict of interest between associated analysts and traders, specifically the potential misuse of investment recommendations. The integration of brokerage and analytical services on financial markets implies that associated brokers may have access to the investment recommendation before it is released to the public, and thus possess an informational advantage. I analyze the possible misuse of this advantage by analyzing the behavior of these participants prior to and after the investment recommendation is issued.

I do not use data from regulatory authorities as other studies do. Instead, I rely on high-frequency data from the Prague Stock Exchange, which allows me to analyze analysts' and traders' behavior on the intra-day frequency. The information contained in this data is used to analyze whether the trading behavior of the associated brokers differs before and after a particular investment recommendation is released. Basically, if we observe systematic patterns over a longer period of time, we can conclude that we are observing the misuse of investment advice. The results confirm that on the Czech capital market the above-mentioned conflict of interest exists and is quite severe.

In the third chapter I analyze the behavior of agents on an atypical financial market – a betting exchange. I focus on the decision making process under risk and uncertainty using data from the world's largest betting exchange, Betfair. Previous studies on this topic have generally attempted to explain the usual characteristic of odd (price) data - *favorite-long shot bias,* where bets on low probability outcome of events provide a lower expected return than bets on high probability outcomes; an observation which is not consistent with standard EUT under the classic risk-averse utility function assumption. The main drawback of these studies on betting markets is the absence of data on *bet size*.

I make several contributions to the literature on decision making under risk and uncertainty. First, I analytically show that bet size is key to the risk preferences of bettors, and that without this information the inference is biased and inconsistent. Using the extensive Betfair dataset I demonstrate that bettors bet different amounts at different odds, and provide corrected estimates of the risk preferences of bettors which, indeed, differ significantly from those of previous studies.

However, this research also has broader implications for the general analysis of behavior under uncertainty, particularly the validity of EUT. The results suggest that, when facing a number of outcomes with different winning probabilities, bettors tend to overweight small and underweight large differences in probabilities, which is in direct contradiction to the linear probability weighting function implied by EUT. These findings can be interpreted as a refinement of Tversky and Kahneman (1992), who report the same behavior of agents with respect to absolute values of probabilities. The results also support the theory of reference points in decision making under uncertainty. However, they indicate that people might use more reference points than the generally accepted 0 and 1, as the outcomes might serve as each other's reference points.

Chapter 1

Detecting Information-driven Trading in a Dealers' Market

Jan Hanousek and František Kopřiva*

CERGE-EI †

Abstract

We focus on the extent of information-driven trading originating from order flows to capture the behavior of market makers on an emerging market. We modify the classic Easley et al. (1996) model for the probability of informed trading using a jackknife approach in which the trades of one particular market maker at a time are left out from the sum of all buys and sells. Using the estimates from the jackknife approach, for each market maker we test whether the order flows associated with the particular market maker behave significantly differently from the others.

Data from the Prague Stock Exchange SPAD trading platform are used to demonstrate our methodology. Finding significant differences in the probability of informed trading computed from order flows, we conclude that order flows can reveal the extent of information-driven trading and could potentially be used by regulatory authorities to identify the suspicious behavior of market participants.

JEL Classification: G14, G15, P34.
Keywords: dealers' market, emerging markets, informed trading, trading systems.

* Email addresses: jan.hanousek@cerge-ei.cz and frantisek.kopriva@cerge-ei.cz.
Address: CERGE-EI, P.O. Box 882, Politických vězňů 7, Prague 1, 111 21, Czech Republic.
The authors would like to thank Jan Bena, Randall Filer, Evžen Kočenda, and seminar and conference participants at Philadelphia, Milano, New York, FMA and MME. GAČR grant (402/08/1376) and Global Development Network grant support are gratefully acknowledged. The views expressed are those of the authors and do not necessarily reflect the position of any of the affiliated institutions.
A previous version of this work has been published in the *Czech Journal of Economics and Finance,* Vol. 61, pp. 204-229. All errors remaining in this text are the responsibility of the author(s).
† A joint workplace of the Center for Economic Research and Graduate Education, Charles University, and the Economics Institute of the Academy of Sciences of the Czech Republic.

1.1 INTRODUCTION

A significant number of studies deal with the issue of insider or informed trading on developed and emerging markets. Starting with the seminal work of Kyle (1985), various models were developed for insider or informed trading and many empirical studies attempted to estimate the severity of this problem. Insider trading can be described as a situation in which the investor is trading based on private information that is available only to a restricted number of people. Although insider trading is illegal in many countries, the distinction between insider trading and informed trading is not as obvious as it may look.[1]

To measure the probability of information-driven trading (PIN) Easley et al. (1996) developed a model now commonly used in the literature that is based on the imbalance of buy and sell order flows. Note that PIN is not exclusively an insider trading measure; it also captures informed trading by investors who are particularly skillful in analyzing public news. It has been shown by Vega (2006), for example, that the estimated PIN was actually higher after company reports become publicly available. There are two main sources of information: information coming from firm fundamentals (including information on mergers and acquisitions) and information coming from order flows. PIN may also be affected by large institutional orders, as their presence may have a substantial impact on market microstructure and the price of the asset, particularly on a small emerging market like the Czech Republic. Overall, the extent of information-driven trading considerably affects the credibility of a given financial market as it also increases the cost of acquiring information on the appropriate timing of a trade.

In the Easley et al. (1996) framework, informed traders act non-strategically and trade upon their inside information. However, informed traders often try to hide their information and react dynamically to the behavior of other market participants, naturally preferring a trading environment with a high degree of anonymity (see Barclay et al., 2003; Anand et al., 2005; Boehmer, 2005; Lee and Yi, 2001 and Brunnermeier and Pederssen, 2005 among others). Hence, an electronic dealers' market is an ideal platform for executing informed trades (see also Sherwood, 1997).

---

[1] While there is a broad consensus that trading on the knowledge of, for example, company profits or disclosures is considered insider trading, there is no similar consensus for trading connected with the execution of large orders or the dual trading practices of some brokers or market makers.

Obviously, trades using private information would not be negligible in size. Let us reiterate that the associated PIN is not necessarily an insider measure as it could also reflect large institutional orders. Typically, on a dealers' market large institutional traders cannot hide their orders and as a result would cooperate with a chosen dealer, therefore sharing information about the total order limits (volume and price). Let us note that the execution of such orders is heavily dependent upon the particular market microstructure. The current literature does not identify the possibility of collusion among market makers and informed traders. Nevertheless, the particular market microstructure may stimulate investors who are executing large trades to share their private information with a particular market maker (MM). This is the case in the Czech Republic.

In the present paper we use the dealers' market (SPAD) of the leading segment of the Prague Stock Exchange, since we believe that the market microstructure of the SPAD trading system might induce the collusion of dealers and large institutional investors. In particular, the MMs and large investors would share private information and, therefore, the order flows coming from a given MM may become a significant source and determinant of information-driven trading on small emerging markets.[2]

The Czech capital market microstructure allows investors to place limit orders only on a dealers' market, whose trading lots are typically of a small size. Further, as the whole market is quite thin, any large order has a significant impact on the price of the underlying asset. Clearly, executing a large trade through market orders by hitting the quotes of MMs would produce with immense trading costs as even a few consecutive orders in the same direction would substantially affect the price. While in practice the use of private information could proceed on several fronts, large institutional orders are likely done via one trading channel, i.e., by using one MM. The fast use of private information may lead to a situation in which several MMs are informed, investors do not behave strategically, and information is quickly captured by the market. On the other hand, large institutional orders could lead to the strategic behavior of the MM, especially on a small market or when liquidity is not large enough.

[2] For example, there are publicly known cases in which the Czech government was selling shares of the energy company CEZ. During a process such as this, one can assume that either the government or the company itself was participating in buying these shares back to keep prices high.

To the best of our knowledge, our study is the first to analyze the extent of order-flow information-driven trading initiated at the level of MMs. We develop a methodology based on the Easley et al. (1996) model to detect the suspicious trading behavior of particular MMs on the Prague Stock Exchange (PSE). By an innovative combination of PIN measurement and a jackknife approach, we leave out the trades of one particular MM at a time from the sum of all buys and sells. We then test the hypothesis that due to private information about a large block order, the MM behaves significantly differently from the other MMs, using the estimates from the jackknife approach. We find significant differences in the behavior of Czech MMs and conclude that the MMs may not only screen out the large informed traders, but on less-regulated emerging markets may greatly affect the extent of information-driven trading coming from order flows by sharing private information with key large customers. Our methodology thus contributes to the detection mechanisms of order-flow patterns which could be used by other investors as well as regulatory authorities. Our results also contribute to current debates on market microstructure and its effect on large and small investors.

1.2 LITERATURE REVIEW

Whenever we talk about informed investors we should distinguish two cases: 1) investors possessing private information originating in firm fundamentals; and 2) investors (brokers) accessing information about large institutional orders. Both cases lead to an increase in order flow imbalance, but as mentioned above the second case would likely involve more strategic behavior of the MM. In addition, the second case is interesting to study in the environment of small stock markets, since it is typically associated with dual trading, information advantages that could last for a longer period, possible stealth trading, etc. Below we present an overview of the relevant literature on information-driven trading, order flows and stealth trading associated with the behavior of dealers or MMs.

The first stream of literature deals with the problem of whether dual traders are informed or not and how they proceed with large orders. Most theoretical studies start with the assumption that dual traders are informed traders and then investigate the effect of their trading strategies (see Roell, 1990 and Sarkar, 1995 among others). Empirical results for developed markets are inconclusive; for example Fishman and Longstaff (1992) viewed dual trading brokers at the Chicago Board of Trade as informed, while Chakravarty and Li (2003), when controlling for the overall trading profit, suggested that dual traders are uninformed.[3] Nevertheless, an overall view of the literature suggests that the MMs or dealers might anticipate private information from the order flow. In addition, informed traders might achieve a more favorable price by breaking up their large orders into multiple medium-sized trades (a so-called "stealth trading" practice, see Barclay and Warner, 1993 for the first reference).[4] The results, however, may vary across different market microstructures; for example, in a pure limit order market (the Stock Exchange of Thailand) informed traders use larger trades compared to dealership markets (Charoenwong, Ding, and Jenwittayaroje, 2010).

The second stream of literature focuses on the overall information advantage of MMs, dealers or brokers rather than on a particular behavior like dual trading. It is well known that MMs facilitate price discovery compared to a pure auction with only public orders and that their informational advantage comes primarily from the obtained order flow (e.g. Madhavan and Panchapagesan, 2000 and Kurov and Lasser, 2004). Typically, the specialists are able to generate short-term trade profits, mostly as a consequence of the bid-ask spread. Nevertheless, in some markets large dealers act more as informed traders than as liquidity suppliers (see for example Wang and Chae, 2003, for a study on the Taiwan Stock Exchange). Since only brokers on the market are able to view the order flow of their customers, the informational advantage of the dealers on the market likely originates from the privileged position of direct access to the electronic exchange without any trading fees or trading delays.

Another stream of literature is devoted to the degree of anonymity on different markets and the associated extent of PIN. For example, comparisons of trades on NYSE and NASDAQ suggest that NYSE, as a less anonymous market, has a lower extent of informed trading (Garfinkel and Nimalendran, 2003). Moreover, the change in listing from a dealership to an auction market (NASDAQ to NYSE or AMEX) leads to a significant decrease in the extent of information-driven trading. Therefore, either specialists on NYSE have a better ability to identify informed traders or the informed

---

[3] The difference between these studies could be associated with the different level of regulation: the earlier study uses data from a period just before the FBI launched a federal investigation into fraudulent trading practices on the Chicago futures exchange.

[4] For more recent results see Anand and Chakravarty (2007) and Anand et al. (2005) among others.

investors prefer to trade on a market with a higher degree of anonymity (Heidl and Huang, 2002). Similar results were obtained by Grammig et al. (2001) from the Frankfurt Stock Exchange via a comparison of non-anonymous floor trading with anonymous electronic trading systems (IBIS and later XETRA), showing that informed traders prefer to execute their orders in the anonymous environment. On the other hand, as pointed out by Jain (2005), electronic trading enhances the liquidity and informativeness of stock markets. Therefore the global access of electronic trading may emphasize the differences between trading systems with market makers and anonymous trading systems.

All of the above-mentioned studies assume that MMs are either using the information from the order flow to act against their customers or screening out informed traders. In addition, the results of Hanousek and Podpiera (2002, 2004) support the hypothesis that MMs in an emerging market (the PSE) may share private information with their key large customers. Furthermore, Hanousek and Podpiera (2004) present more intriguing results: Despite many improvements in regulation and increased trading volume the extent of information-driven trading was nearly the same for the years 1999 and 2002. They point out that the extent of informed trading was about the same for shares of Ceska sporitelna and Erste Bank.[5] Let us note that these stocks have little in common except for having the same set of MMs, therefore, one could ask to what extent the MMs on the PSE affect the probability of informed trading.

The studies reviewed above suggest that the behavior of informed traders differs according to market microstructure, and that MMs are important participants on the market in that they are able to recognize informed traders. Several studies demonstrate the ability of MMs to identify informed traders and the effect this has on the probability of information-driven trading. They conclude that a higher degree of anonymity is associated with a higher probability of information-driven trading, and that informed and insider trading is a widespread practice in emerging financial markets.

[5] In 2000, Ceska sporitelna (a major Czech bank) was privatized to the Austrian Erste Bank. Erste Bank, already listed in Vienna, started dual listing on the PSE in October 2002.

1.3 Methodology

1.3.1 The Easley et al. (1996) model

Our model is based on the well-known framework developed by Easley et al. (1996). We first briefly review their model and then introduce our extension. In all steps of our model, as well as in any empirical estimation, we control for the order flow size by assuming/using a regular lot as a trading unit.

There exist three types of agents on the market: uninformed (noisy) traders, informed traders, and MMs. Trading is divided into *n* separate trading days. See Figure 1.1 for a tree diagram of the trading day. Before each day an information event might occur. An information event is defined as the occurrence of a signal *s* about the value of the asset. The probability that a signal occurs is α, and if a signal occurs, it takes on two possible values: low with probability δ and high with probability $1-\delta$.[6] If a signal occurs, some fraction of the traders receive the signal. If no signal occurs, all traders stay uninformed. Using the scheme of Figure 1.1 we can express the probability of observing a given number of buys and sells as

$$\begin{aligned} L((B,S)\,|\,\theta) = {} & (1-\alpha) * e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} && (\textit{no event day}) \\ & + \alpha\delta * e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-(\mu+\varepsilon)T}\frac{((\mu+\varepsilon)T)^S}{S!} && (\textit{bad event day}) \\ & + \alpha(1-\delta) * e^{-(\mu+\varepsilon)T}\frac{((\mu+\varepsilon)T)^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} && (\textit{good event day}) \end{aligned} \tag{1.1}$$

where *S* is the number of sells and *B* the number of buys. The first part of expression (1.1) denotes a no event day, the second part a bad event day and the third part a good event day. According to the assumptions of the model the days are independent and therefore the probability of observing a series of days with a given sum of buys and sells for each day is a product of the probability for the individual days.

$$L(B_1, S_1, \ldots, B_I, S_I\,|\,\theta) = \prod_{i=1}^{I} L((B_i, S_i)\,|\,\theta)\,. \tag{1.2}$$

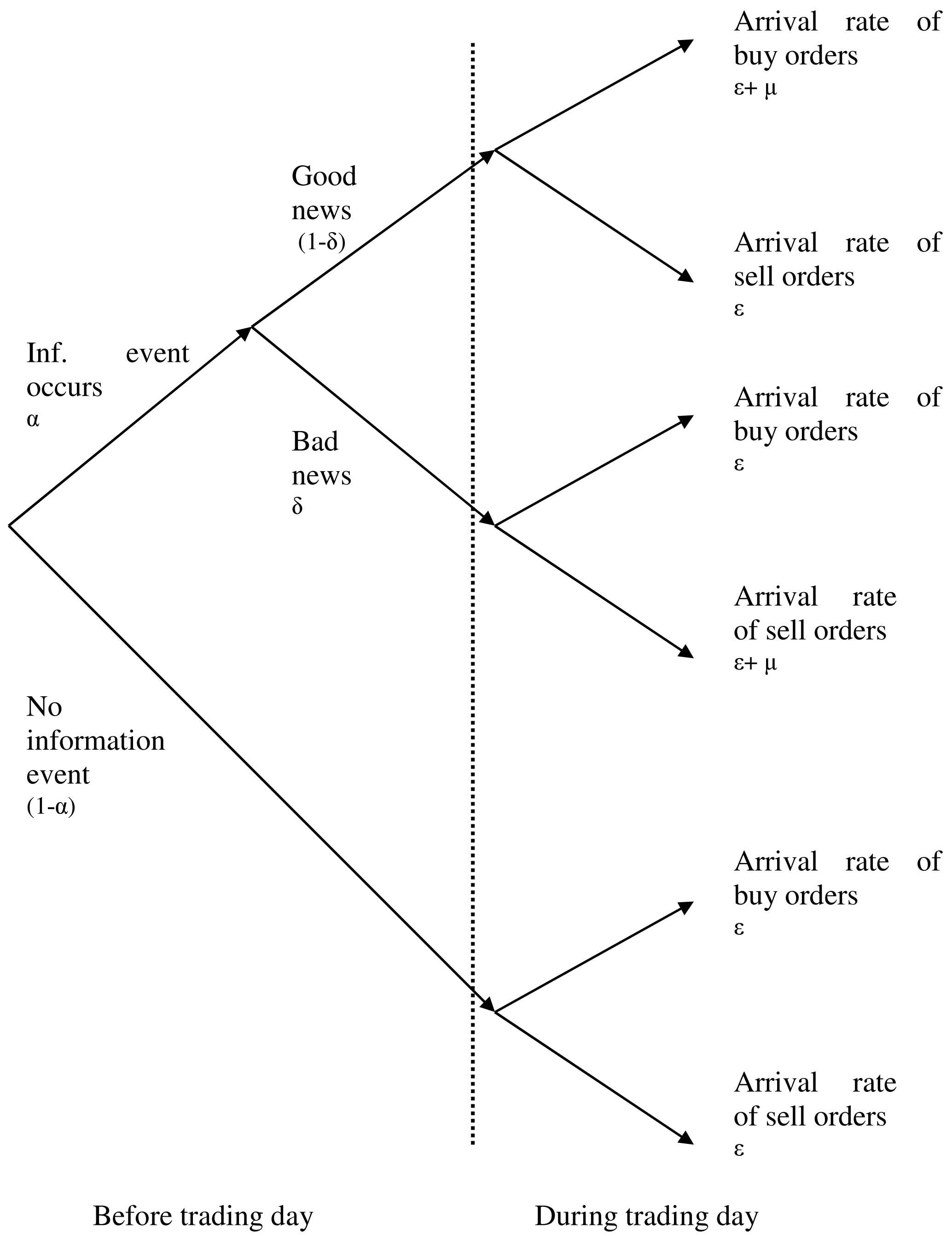
The parameter $\theta = (\alpha, \delta, \varepsilon, \mu)$ is then estimated using the maximum likelihood method.[7]

---

[6] In the case of a bad signal the value of the asset is $\underline{V}$, for a good signal $\overline{V}$ and for no signal unchanged.

[7] For the estimation we used a rearranged log likelihood function as presented in Easley et al. (2010).

Figure 1.1: Trading day tree diagram



Note: The diagram depicts the structure of arriving buy and sell orders during a trading day, where α is the probability of the information event occurring, δ is the probability of bad news, μ is the arrival rate of informed traders and ε is the arrival rate of uninformed traders.

The probability of information-driven trading is the chance that a MM will trade with the informed trader and therefore can be computed as a ratio of the arrival rate of informed traders and the arrival rate of all traders:

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}. \tag{1.3}$$

This is actually the conditional probability of an information-driven trade given the occurrence of a trade at the beginning of a trading day. Therefore the numerator is the product of the probability of an information event times the arrival rate of informed traders. The denominator is then the probability of the occurrence of a trade, which is the probability of an incoming informed trader plus the probability of an incoming uninformed buyer and seller.

1.3.2 LARGE BLOCK TRADES AND INFORMED MMS

Our extension of the original model reflects the characteristics of a quote-driven market with a relatively small number of MMs. These MMs also usually act as brokers. As on every market, there are also various types of investors. We roughly divide them into two groups: large (institutional) investors and small (retail) investors. As these types of investors often have different needs, the MMs (brokers) are specialized on various types of investors or have at least a different approach to these investors. Small investors often open an account at just one broker and either use online trading systems to execute their orders by hitting the quotes posted by MMs or use some of the brokerage services.

Large investors, by contrast, have specific needs in order to execute their large orders, as these orders often have a significant price impact. Large investors are therefore insiders, since they possess valuable private information (coming from the order flow) which has a significant effect on the price of the asset (Chakravarty, 2001 and Golec, 2007 among others). According to their size, they are the key customers for the brokers. Large investors may thus get special brokerage services, and the fees for executing orders may differ significantly from those of retail customers. According to Schwartz and Shapiro (1992), large institutional investors accounted for 72% of the share volume on the New York Stock Exchange; given the relatively low number of retail investors in the Czech Republic, this percentage might be significantly higher on the PSE.

On some markets, the problem of the different needs of different types of investors and the potential problem of better-informed large investors with a large impact on prices is solved by an upstairs market (Golec, 2007). However, similar to the market microstructure of the Czech capital market, in our model there is no upstairs market for large orders. Large investors thus often face a decision between checking the price and hiding the trade. Similar to the existing literature on stealth trading, we expect that large orders are usually broken into medium-size trades. As large investors face a decision on how to optimize the execution costs of their orders, using market orders (similar to small investors) to execute large trades is generally not suitable for them due to the large impact on the price and therefore the large execution costs. Thus, large investors may often prefer passive trading strategies, i.e. using limit orders. Nevertheless, on the quote-driven market only MMs may place limit orders (quotes). Therefore, large investors are forced to seek lower execution costs by negotiating with MMs. In other words, to optimize the execution costs of their orders, large investors are, in our model, compelled to negotiate with MMs about the possible execution of the orders, and MMs may exploit market making activities in order to execute these orders. There is latitude for collusion, or large investors could be pressured to cooperate and share their information with the MM. Some of these scenarios are described by Keim and Madhavan (1995), Chan and Lakonishok (1995), and Golec (2007) and confirm that larger trades may take several days to execute.

Such implementation of large trade orders has a greater chance of minimizing the impact on the stock price; practically it means that the MM trades against his account and once he secures the deal (accumulates or sells shares) then a block trade with his client closes the trade. As in this scenario MM’s activities are used to hide the large trade, it is not rational for the large investor to contact more than one market maker/broker since this would spread the information about an incoming large order. Therefore, at the beginning of the execution of his large order, the large investor chooses a trading channel, meaning he chooses a MM, which we can identify in our dataset. In other words, the MM has an incentive to act strategically in choosing the optimal timing of several trades to process the whole large order at the best possible price.[8]

Our model, therefore, consists of two types of private information. The first is the private signal in the Easley et al. (1996) model: short-lived information about the underlying asset that is available to a relatively large number of informed investors. Similar to Keim and Madhavan (1995), we assume that in such a situation investors prefer market orders and execute their trades as quickly as possible. In other words, they do not act strategically, but come to the market as a result of the private information they received. The second type of private information in our model comes from the order flow. Information about the incoming large order is available only to the large investor and the MM with whom the large investor is negotiating about the optimal execution of the trade. Whereas the institutional investor announces the number of shares and the side of the trade, the broker tries to execute the order with the lowest possible execution costs. Similar to Keim and Madhavan (1995), we assume that an investor who possesses longer-term private information available only to a restricted number of people prefers to trade more discreetly, negotiating with some of the MMs on the preferable execution of the trade. Also, large orders executed through MMs have large price impacts and, therefore, using limit orders may significantly reduce the execution costs of the trade. Keim and Madahavan (1995) argue that the benefits of a passive trading strategy (limit orders) should be largest on thin markets where liquidity is low. Their analysis of the data on the equity transactions of 21 institutions shows that the execution time of trades is longer than one day: on average 1.65 to 1.80 days. However, this might be significantly higher for the Czech Republic due to the lower size of the market.

The first type of information flows to the market through market orders and therefore its revelation is not affected by the behavior of particular MMs. On the other hand, the large investor, to optimize his execution cost, chooses one of the market makers/brokers, who then executes his order and thus has other incentives than to balance his portfolio. In such a situation we in fact have two types of MM: informed and uninformed.

[8] However, we do not expect that the MM is necessarily trying to manipulate the price or is abusing the market illegally.

Suppose that there is other information affecting the price of an asset: information about a large order that is independent of the above private signal of informed investors and that lasts for several trading days. In such a situation the large investor will contact just one MM, as otherwise he would be spreading the information to other participants in the market, which could increase the execution costs of the trade. Therefore we assume that only one informed MM has private information about this large order coming on the market from one of his clients. The large order consists of a random volume of shares and a random length K of trading days. Note that the actual number of days and the total number of shares can be limited by the price ceiling imposed by the client or/and by a particular deadline.[9] As confirmed by several brokers, the typical practice is that a large order is inspected at the end of the trading session and new limits are set for the next day(s) or the execution of the order is stopped. In such a situation only one MM will have detailed information about the large order, i.e. private information. If more than one MM receives information about the large order and if the MMs do not act in consonance with each other, the order will be revealed to the whole market and the new value of the asset will be revealed immediately by the competitive behavior of two or more informed MMs.[10]

If the MM is informed, we assume that he does not set quotes in a way that would immediately reveal his information about the order. Therefore, in the case of a large buy order the informed MM will strive to have the best quote[11], that is, he will post his quotes for buys more actively and ultimately obtain the best quote with a higher probability than the uninformed MM. Although the other MMs may suspect the existence of the large order, they do not know the exact information of the trade, i.e. the limit price and the execution deadline. This is key information if the other market participants are to actively post quotes for buys and compete with the informed MM. Without this information, there is a risk that the MM would immediately stop the execution of the trade and the price would be too high.

---

[9] Even though block trades must be reported in 5 minutes in the open session and in 60 minutes in the closed session, the behavior of MMs suggests that they are either aware of the block trade in advance or set the block trade *ex-post*.

[10] Given the trading environment (a dealers' market) we expect a relatively low number of MMs, therefore, due to the competition of two or more informed MMs we expect that the information about the large order will be revealed quickly.

[11] The best buy and best sell quotes from all the market maker's quotes.

Further, the uninformed MMs might find it difficult to compete with the price setting of the informed MM as they do not possess the inventory advantage of the informed MM. Without inside information about the large order, the uninformed MMs will work to avoid risky unbalanced positions and will post quotes such that they would finish with somewhat balanced inventories. On the other hand, the informed MM, contingent on his information, might venture riskier positions from the point of view of uninformed MMs and therefore might be able to afford to actively quote only buys or sells. The uninformed MMs generate profit from the trading fees and spread; the informed MM, however, generates additional profit from proprietary trading. Thus he may compel the other MMs either to accept a lower spread and thus lower trading profits, or to give up market making activities for the particular stock. For the other investors it is also quite hard to trade upon just part of the information — the information that one of the MMs might be executing a large order — as they would face the spread costs while trading with only this incomplete information. They could, however, use such information to postpone the execution of their trade.

Under these circumstances, the informed MM is likely to use his market making activities to execute the trade and thus will likely have a different balance of mandatory buys and sells than the remaining MMs. Although the other market participants might be aware of the presence of a large order it could be difficult to use this information in the current trading system. Since the uninformed MMs have limited resources and therefore must balance their inventory position, it is especially difficult for them to compete with the informed MM. Even if an uninformed MM wished to trade using this information, he would face the risk that the large investor would stop selling the share. Again, the typical practice is that the large order is inspected at the end of the trading session and new limits are set for the next day(s). It is this — the restricted access to the limit orders of all investors, uninformed MMs with limited capital who raise money mostly from the spread, the non-existent upstairs market, and the possibility of non-transparent pseudo block trades that move from block trades into the SPAD segment — that makes the market microstructure quite messy and enables some MMs to use their market making activities to hide the information stemming from large trades.

Overall, since the major source of income for an MM is generated by the spread between the bid and ask prices, an existing large trade conducted via a specific MM could lead to 1) collusion; 2) the other MMs' spreads being close to their marginal costs; and/or 3) other MMs stopping trading. The informed MM, on the other hand, will trade actively only on one side (buy or sell), according to his private information. By and large it leads to a market with lower competition and wide latitude for price manipulation.

The situation is well illustrated on the example of the publicly known case of the Czech government selling shares of the energy company CEZ. The publicly available information was that the Czech government started selling nearly 7% of its shares in September 2007 and stopped selling shares due to the financial crises in September 2008. One of the commissioners helping the Czech government with the execution of the trade was MM4.[12] The overall volume of the trade was around 4 billion CZK, i.e. 9% of the total volume traded between September 2007 and September 2008 (see Table 1.1). Comparing the trading volumes by category, one can speculate that only a part of the governmental deal was conducted through mandatory trades; most trades during this period likely used the MM4 quotes as an indication of the limit orders of the Czech government.

Table 1.1: Total traded volume and mandatory trades, Czech government selling shares of CEZ

Time Span	Total Volume (bil. CZK)	Mandatory Trades
Sep 07–Aug 08	373.9	148.8 (upper: 76.6; lower: 72.2)

Note: In the Mandatory Trades column, the main number is the overall volume; the number in the upper right corner is the mandatory buy volume; and the number in the lower right corner is the mandatory sell volume.
Source: www.akcie.cz and authors' computations.

Table 1.2: Mandatory trades of particular MMs, Czech government selling shares of CEZ

MM	MM1	MM2	MM4	MM5	MM6	MM7	MM9	MM10	MM11
Sep 07–Aug 08 (upper)	9.7	6.4	18.3	5.5	8.5	11.1	6.0	7.0	4.2
Sep 07–Aug 08 (main)	1.8	0.6	10.4	0.1	-0.8	-3.8	0.5	-4.5	0.0
Sep 07–Aug 08 (lower)	7.8	5.8	7.9	5.3	9.3	14.9	5.5	11.5	4.2

Note: In each column the main number represents the difference between mandatory buy and mandatory sell volume while the number in the upper right corner is the mandatory buy volume and the number in the lower right corner is the mandatory sell volume.
Source: www.akcie.cz and authors' computations.

[12] We coded all the MMs in order to minimize possible bias in computations and analyses. The coding of market makers is available upon request.

Further, the fact that during this period the percentage of the market share of MM4 increased to 18% (overall 13% for CEZ) supports our hypothesis that inventory advantage and detailed private information about large orders give the informed MM the opportunity to trade more actively and to end up with an unbalanced inventory position (see Table 1.2). The execution of the trade ended with the first large price jump in September 2008, which also supports the notion that a large order is inspected at the end of the trading session and stopped when the price changes significantly. If any uninformed MM wishes to trade using the publicly available information that the Czech government is going to sell its shares, he would face the risk that MM4 would stop selling the share.

This is likely what we see reflected in the behavior of the MMs as the governmental deal was conducted, since the price remained constant for nearly the whole period. MM4 was significantly more active on the quotes for buys (MM selling the asset) while MM7 and MM10 (large MMs) were mostly active on the quotes for sells (MM buying the asset).

1.3.3 ESTIMATION PROCEDURE

To estimate the extent of information-driven trading due to large orders or, in other words, due to informed MMs, first we run estimations for the whole sum of buys and sells. Further, to estimate the PIN originating from large orders or other private information of the MMs we propose a procedure to estimate the PIN with and without the trades of informed MMs. Therefore, we exclude one by one each MM's trades from the sum of buys and sells and estimate the model. Having all the parameters $\theta_i = (\alpha_i, \delta_i, \varepsilon_i, \mu_i)$ estimated for each MM, we then test whether PIN using the estimated parameters $\theta = (\alpha, \delta, \varepsilon, \mu)$ and PIN without considering the trades of a given MM are significantly different.

Both estimators of PIN have asymptotically normal distributions and the estimators are positively correlated. We therefore use a cluster modification of the sandwich estimator as proposed by Rogers (1993) to estimate the joint covariance matrix of both estimators.

Having identified the informed MMs, we can estimate the effect of large orders on the probability of information-driven trading:

$$PIMM = \left| \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} - \frac{\alpha_i \mu_i}{\alpha_i \mu_i + 2\varepsilon_i} \right|, \qquad (1.4)$$

where $\theta = (\alpha, \delta, \varepsilon, \mu)$ are the estimated parameters from the classic Easley et al. (1996) model using the sum of all buys and sells for each day, and $\theta_i = (\alpha_i, \delta_i, \varepsilon_i, \mu_i)$ are the estimated parameters using the sum of all buys and sells for each day without the trades of a given identified informed MM. The extent of information-driven trading stemming from the behavior of an informed MM is therefore the difference between the probability of informed trading with and without the trades of the informed MM.

1.4 DATA

For our analysis, we use intra-day data from the Prague Stock Exchange (PSE) SPAD trading system for all stocks traded from 1 January 2003 to 31 August 2010, publicly available online.[13] SPAD was founded in 1998 to increase the liquidity of the market. The trading system is designed as a dealers' market with at least three MMs for each stock, who are required to quote ask and bid prices for a standardized number of shares with a limited maximum possible spread for each stock. If a given quote is the best available on the market, the particular MM is obliged to trade on the posted quote for a buy or sell.

Each trading day is divided into two phases, open and closed. Actual trading occurs during the open phase of the system, from 9:15 a.m. to 4:00 p.m. each trading day. We use data on all SPAD trades during the sample time period. Each trade record in our database consists of security identification, date, time, type of trade, and price, and for the standard SPAD trades also the identification of the MM who traded it. We are also able to identify cross trades and trades conducted between the inventory of the MM and the MM's client. Even though akcie.cz provides quite detailed information on trades, a significant proportion are nevertheless not transparent, as the mandatory trades are only around 40% of the total traded volume. Despite the increased regulation of block trades, these trades likely just moved from the segment of block trades into the non-transparent segment of SPAD trades with no identification. A key advantage of our

[13] Available at www.akcie.cz. The last access for this paper was on 30 September 2010.

dataset is that we are able to identify not only whether the given trade was buyer- or seller-initiated but also which MM was on which side of the trade.

The sample period consists of 1925 trading days. We focus on 15 companies traded during that period (see Table 1.3a and Table 1.3b in the appendix for descriptive statistics of market capitalization and traded volumes; KIT DIGITAL was traded only for a short period in our dataset).[14] We have eleven MMs in our sample period: six brokerage firms and five banks.[15] The MMs also differ in their specialization in different types of customer: retail vs. large institutional investors.

As can be seen from Table 1.3a and Table 1.3b none of the eleven MMs on SPAD had a significantly higher market share in any of the analyzed stocks. The maximum market share reached about 30% for one MM and each traded stock had at least five MMs with a more or less comparable market share. The average number of trades during a day differs significantly among the stocks during the sample period. Only some of the newly introduced stocks attracted the attention of investors quickly, and the activity of some of these new blue chips on the PSE was not comparable to those of the already established stocks. Our model assumes the significant role of block trades as a source of information for some MMs; the data appear to confirm this assumption. Block trades are defined by a limit set by the PSE, and this limit is considerably larger than the market capitalization of the trading lots in SPAD. According to current regulation every block trade has to be registered within 5 minutes during the open phase (9:15 a.m. to 4:00 p.m.) and within 60 minutes during the closed phase.

Table 1.5 (in the appendix) clearly shows that a significant percentage of the volume traded on SPAD used block trades. We might speculate that between 2003 and

---

[14] Only six of them were traded during the whole period: two banks (Erste Bank and Komercni banka), a petrochemical company (Unipetrol), an electricity producer (CEZ), a telecommunications company (Telefonica O2) and a cigarette producer (Philip Morris). Another telecommunications company (Ceske Radiokomunikace) was removed from the market in September 2004. One IPO, Zentiva, was introduced to the market in June 2004 and removed from the market in April 2009. In February 2005 a real estate company (ORCO), already listed in Paris, started dual listing on the PSE and in June 2005 a media company (CME), already traded on NASDAQ for over 10 years, started dual trading on the PSE. ECM (a real estate company) and PEGAS (a synthetic non-woven textiles producer) were introduced in December 2006, AAA (a car reseller) in September 2007, NWR (a coal mining company) in 2008 and VIG (an insurance company) in 2008.

[15] The brokerage firms are ATLANTIK financni trhy, a.s., BH Securities a.s., CA IB Securities, a.s., Fio, burzovni spolecnost, a.s., Patria Finance, a.s. and WOOD & Company Financial Services, a.s.; the banks are Ceska sporitelna, a.s., HVB Bank Czech Republic a.s., Raiffeisenbank a.s., ING Bank N.V. and Komercni banka, a.s.

2005, during which time there was a high percentage, the MMs who were focused on large customers also used standard SPAD trades to gather stocks in order to execute block trades. Such MMs are actually informed traders, and thus the block trades may have been an indication of a high level of private information on the PSE. The significant decrease in the percentage of block trades in 2006 was likely caused by the increased regulation of MMs.[16] Despite this increased regulation, the suspicious practices of unidentified block trades are still present. The forbidden unidentified block trades have moved to the segment of the SPAD market with no identification of the trading parties, leading to a situation similar to the one before 2006 (see Table 1.5). Therefore, trading practices probably remained the same; only the placement and reporting of the trades changed.

SPAD was introduced to increase liquidity on the PSE. However, due to the size of the trading lots only medium and large investors could trade in the system. As Table 1.6 (in the appendix) demonstrates, the trading lots have varied quite a lot since over the sample period the prices of some stocks grew significantly. For example, the smallest trading lot (AAA) started at 0.01 million CZK, while the largest lot was 7.18 million CZK (CEZ).[17] Such a variance in mandatory minimum trading volume is another problem of the SPAD trading system, as it might present obstacles for uninformed and smaller investors; the design of the market thus attracts mostly large institutional and informed investors. For this reason the effect of changing the lot size can significantly affect the extent of information-driven trading, as according to the Easley et al. (1996) model informed traders are more likely to trade larger volumes. Regarding the significant increase of retail investors in the Czech Republic, therefore, reducing the lot size might attract more uninformed investors since on SPAD the fees are considerably lower than other trading channels.

1.5 RESULTS

For trading on the PSE in general, we observe that the structure of potential investors and the behavior of MMs follow different and unique patterns during the morning and afternoon sessions; we therefore estimate the extent of information-driven trading for

[16] As of early 2006, all MMs and brokers are obligated to report their activities to the regulation authority, including their dealings book.

[17] Using the average exchange rate to USD over the period studied (~23.7 CZK=1 USD), the lot size varies from 25,000 to 232,000 USD.

each session separately. New information comes to the Czech capital market before the morning session and then again in the afternoon when there is news from U.S. capital markets. As the lull in information means only a negligible fraction of trades takes place between 12:00 p.m. and 2:00 p.m., and even these are mainly automatic, we divide each day into two main parts: the morning session from 9:15 a.m. to 12:00 p.m. and the afternoon session from 2:00 p.m. to 4:00 p.m., to better reflect trading patterns and the specific nature of a small emerging market with a substantial foreign presence.

For (automatic) identification purposes we first run a rolling window of 90 trading days through our sample period and for each window estimate the extent of information-driven trading. We believe that the 90-trading day window is an optimal balance between the assumption of the underlying Poisson process being stationary and the length of the estimation moving window, which affects the precision of estimates.[18] Results are graphically presented in Figures 1.2 and 1.3 (in the appendix). Based on the patterns visible in these figures, we focus on particular stocks for which the rolling window analysis suggested significantly different behavior of particular MMs. While inspecting these figures, we could observe that for shares for which the PSE is the main market, the afternoon sessions always show higher PIN. By the same token, the dual-traded shares show just the opposite pattern, i.e. the morning session has higher PIN. Possibly due to the strengthening of the regulation of the MMs by introducing the requirement to regularly report detailed information about their activities, the extent of information-driven trading was decreasing significantly until 2008, at which time the large decrease of traded volume due to the financial crisis again increased the PIN of most stocks.

Our trading data consists of precise information on whether the trade is a mandatory buy or mandatory sell, contrary to most existing studies.[19] Boehmer et al. (2007) point out, however, that using an estimation based solely on whether the trade is buyer- or seller-initiated leads to downward-biased PIN estimates and that the magnitude of the bias is related to the trading intensity of the securities. This may partly explain why our results differ from the results of Hanousek and Podpiera (2004), who

[18] We have run the estimation also for shorter rolling windows. Our results suggest that that the 90-day rolling window still satisfies the assumptions of the model, as the results are similar. Detailed results are available upon request.

[19] If the quote is the best available on the market and if some investor reacts to it, the MM is obliged to execute the trade.

used data for the whole day and estimated whether the trade was buyer- or seller-initiated using Lee and Ready's (1991) methodology. Hanousek and Podpiera (2004) saw no improvement in the extent of information-driven trading between 1999 and 2002. Nevertheless, our results suggest that all the blue chips experienced a significant decrease in PIN between 2003 and 2006.

In Tables 1.7a and 1.7b (in the appendix) we present the results of tests for the time periods and stocks identified in the automatic identification phase described above. Rejecting the null hypothesis of the equality of the estimates means that the MM has a considerable imbalance between his mandatory sells and buys and hence that his behavior differs from the behavior of other MMs during the particular time period. PIMM tests how different the average trade imbalance of buys and sells of a particular MM is relative to the average trade imbalance of buys and sells on the market as a whole. By taking a different position on the balance of buys and sells, the MM is possibly hiding some relevant information from the market or is executing a large block order for his customer. Overall, our results suggest that during our sample period there were several MMs who behaved with marked differences from the other MMs.[20]

The second columns of Tables 1.7a and 1.7b show the identified time period for the particular stock. To demonstrate the practical use of the method, all identification and estimation was done using a 90-day trading window. It is striking that most of the identified periods coincide with significant events or with news related to the particular stock. First we discuss the results for Ceske Radiokomunikace (CRA), which was removed from the market in September 2004 although the decision on removal had to be made in 2003. Therefore, our results that MM4 behaved very differently from other MMs in the second half of 2003 may suggest that he cooperated with some large informed customer who had better information about the buyout of CRA.

Similarly, results for Telefonica O2 resonate with its privatization, indicating that some investors may have been aware of the privatization and traded on this information ahead of time (see Figure 1.2 in the appendix for a summary of the test: MM7, afternoon). A further example of coincidence with important news is the result for CEZ. As we already mentioned, during 2008 the Czech government sold nearly 7% of its shares and our results confirm that part of the trade was done using MM4's

[20] The difference does not imply that the MM is an insider, as he may be processing a large trade order or using dual trading, which is not illegal in the Czech Republic.

market-making activities. The other results for CEZ are also connected with important news: during the summer of 2009 the Czech parliament approved a law on distributing free carbon dioxide permits for firms, including CEZ.

Other examples of important news that coincide with our results include the information about NWR buying a 25% share in Ferrexpo late in 2008. In the case of CME, both the uncertain outlook of the firm after the financial crisis and, more importantly, information about Warner Brothers buying a 31% share in it constituted sufficiently important news to possibly have large orders traded through MM1 during the spring and summer of 2009. The financial crisis and the collapse of capital markets decreased the traded volume and therefore also increased the effect of every larger order on the price of the assets. This, together with speculations of whether ORCO would survive its financial problems, would support our results showing markedly different behavior of MM5, MM1 and MM7 between 2009 – 2010 for ORCO.

Our results confirm that a high percentage of block trades (around 30%) or large orders might have a significant impact on the behavior of some MMs, as seen for CEZ, Komercni banka and Phillip Morris between 2003 and 2005. Although the percentage of block trades decreased remarkably in 2006, the behavior of MMs likely did not change, as the SPAD trades with no identification experienced a significant increase at the same time. Our results suggest that even though market participants might be aware of the different behavior of several MMs, they are not able to compete with them due to the better information coming, for example, from detailed information about large orders.

Lastly, we focused on the effect of changes in trading lot size on trading behavior and on PIN. As already mentioned, changing the lot size may affect the extent of information-driven trading since the informed traders are more likely to trade larger volumes. Smaller lot volumes might attract more uninformed investors. The estimation and test results are summarized in Table 1.8 (in the appendix). As can be seen, most of the changes in lot size had a considerable effect on the extent of information-driven trading, as lot breakups attracted more retail and therefore more uninformed investors. Overall, smaller lot size means more trades with the particular stock, higher attractiveness for individual investors, and lower PIN. The exception is Erste bank (EB), whose shares did not react strongly to either an increase or a decrease in the lot size. In terms of information-driven trading, this is still consistent since the primary market of

EB is the Vienna Stock Exchange and trading in Prague is much smaller than in its main market.

1.6 CONCLUSION

In this paper we analyze the behavior of MMs and their ability to maintain private information about large orders. We propose an automatic procedure using order flows to detect and test specific positions of particular MMs in an electronic dealers' market. Trading data with one side of the mandatory buy/sell trade orders identified are used to demonstrate our method.

We found significant differences in behavior among MMs on the Prague Stock Exchange, supporting the notion that they play a dominant role in affecting the price for a short time interval as well as for a longer period. Although the other participants in the market may suspect that some MMs possess private information about the value of the asset, they are not able to reveal the full information. Further, our analysis confirms that important changes such as decreasing the volume of the trading lot may affect (decrease) the extent of order flow information-driven trading.

From the trading perspective, it could be argued that on a thin market MMs should be allowed to maintain private information about their sizable (block) orders so as to face threats of predatory trading and increased volatility during such trades. Nevertheless, the current practice of MMs in the Prague Stock Exchange could threaten minority and uninformed investors because prices then no longer convey all relevant information. This observation leads to the conclusion that further regulation might be beneficial; however, optimal policy from the regulatory point of view is not straightforward and is beyond the scope of the present paper. From our estimations it seems clear, though, that increased regulation by introducing so-called trading books (a detailed recording of all conducted trades) for each broker does not help. As discussed in this paper, (forbidden) block trades were basically transformed into SPAD trades with missing party identification. This might suit some large institutional players, but we believe that it results in a less transparent market with lower trading volume and lower informational content, which is potentially harmful especially on a market with a significant presence of foreign investors. This raises questions about the introduction of an upstairs market (similar to NYSE, for example), a transparent trading segment that would serve institutional investors while keeping a variant of SPAD with smaller lot size suitable for small individual investors. It seems clear from our results that an appropriate (i.e., much smaller) size of trading lot would reduce the amount of information-driven trading, and also would increase the trading volume and attract small individual investors.

Given that this study uses an automatic procedure, has only modest assumptions, and employs a model that is relatively easy to use, we believe that the methodology in this paper could be taken up by investors as well as regulatory authorities on emerging markets to identify unusual order flows and/or detect the suspicious behavior of particular market participants.

1.7 BIBLIOGRAPHY

Anand, A., Chakravarty, S., and Martell, T. (2005). Empirical evidence on the evolution of liquidity: Choice of market versus limit orders by informed and uninformed traders. *Journal of Financial Markets,* Vol. 8 No. 3, pp. 289-309.

Barclay, M. J., Hendershott, T., and McCormick, D. T. (2003). Competition among trading venues: Information and trading on electronic communications networks. *Journal of Finance,* Vol. 58 No. 6, pp. 2637-2665.

Barclay, M. J. and Warner, J. B. (1993). Stealth trading and volatility: Which trade move prices? *Journal of Financial Economics,* Vol. 34 No. 3, pp. 281-205.

Boehmer, E. (2005). Dimensions of execution quality: Recent evidence for US equity markets. *Journal of Financial Economics,* Vol. 78 No. 3, pp. 553-582.

Boehmer, E., Grammig, J. and Theissen, E. (2007). Estimating the probability of informed trading - does trade misclassification matter? *Journal of Financial Markets,* Vol. 10 No. 1, pp. 26-47.

Brunnermeier, M. K. and Pederssen, L. H. (2005). Predatory trading. *Journal of Finance,* Vol. 60 No. 4, pp. 1825-1863.

Chakravarty, S. (2001). Stealth-trading: Which traders' trades move stock prices? *Journal of Financial Economics*, Vol. 61 No. 2, pp. 289-307.

Chakravarty, S. and Li, K. (2003). A Bayesian analysis of dual trader informativeness in futures markets. *Journal of Empirical Finance,* Vol. 10 No. 3, pp. 355-371.

Chan, L. K. C. and Lakonishok, J. (1995). The behavior of stock prices around institutional trades. *The Journal of Finance*, Vol. 50 No. 4, pp. 1147-1174.

Charoenwong, C., Ding, D.K., and Jenwittayaroje, N. (2010). Price movers on the stock exchange of Thailand: Evidence from a fully automated order-driven market. *Financial Review,* Vol 45, pp. 761-783.

Easley, D., Kiefer, N. M., and O'Hara, M. (1996). Cream-skimming or profit-sharing? The curious role of purchased order flow. *Journal of Finance,* Vol. 51 No. 3, pp. 811-833.

Easley, D., Hvidkjaer, S., and O'Hara, M. (2010). Factoring information into returns. *Journal of Financial and Quantitative Analysis,* Vol. 45 No. 2, pp. 293-309.

Fishman, M. J. and Longstaff, F. (1992). Dual trading in futures markets. *Journal of Finance,* Vol. 47 No. 2, pp. 643-671.

Garfinkel, J. A. and Nimalendran, M. (2003). Market structure and trader anonymity: An analysis of insider trading. *Journal of Financial and Quantitative Analysis,* Vol. 38 No. 3, pp. 591-610.

Golec. J. (2007). Are the insider trades of a large institutional investor informed? *Financial Review*, Vol. 42 No. 2, pp. 161-190.

Grammig, J., Schiereck, D., and Theissen, E. (2001). Knowing me, knowing you: Trader anonymity and informed trading in parallel markets. *Journal of Financial Markets,* Vol. 4 No. 4, pp. 385-412.

Hanousek, J. and Podpiera, R. (2002). Information driven trading at the Prague stock exchange: Evidence from intra-day data. *Economics of Transition,* Vol. 10 No. 3, pp. 747-759.

Hanousek, J. and Podpiera, R. (2004). Czech experience with market maker trading system. *Economic Systems,* Vol. 28 No. 1, pp. 177-191.

Heidl, H. G. and Huang, R.D. (2002). Information-based trading in dealer and auction markets: An analysis of exchange listings. *Journal of Financial and Quantitative Analysis,* Vol. 37 No. 3, pp. 391-424.

Jain, P. K. (2005). Financial market design and equity premium: Electronic versus floor trading. *Journal of Finance*, Vol. 55 No. 6, pp. 2955-2985.

Keim, D. B. and Madhavan, A. (1995). Anatomy of the trading process: Empirical evidence on the behavior of institutional traders. *Journal of Financial Economics*, Vol. 37 No. 3, pp. 371-398.

Kurov, A. and Lasser, D. (2004). Price dynamics in the regular and e-mini futures markets. *Journal of Financial and Quantitative Analysis,* Vol. 39 No. 2, pp. 365-384.

Kyle, A. (1985). Continuous auctions and insider trading. *Econometrica,*Vol. 53 No. 6, pp. 331-359.

Lee, C. and Ready, M. (1991). Inferring trade direction from intraday data. *Journal of Finance,* Vol. 46 No. 2, pp. 733-746.

Lee, J. and Yi, C. H. (2001). Trade size and information-motivated trading in the options and stock markets. *Journal of Financial and Quantitative Analysis,* Vol. 36 No. 4, pp. 485-501.

Madhavan, A. and Panchapagesan, V. (2000). Price discovery in auction markets: a look inside the black box. *Review of Financial Studies,* Vol. 13 No. 3, pp. 627-658.

Roell, A. (1990). Dual capacity trading and the quality of the market. *Journal of Financial Intermediation,* Vol. 1 No. 2, pp. 105-124.

Rogers, W. H. (1993). sg16.4: Comparison of nbreg and glm for negative binomial. *Stata Technical Bulletin* 16: 7 Reprinted in Stata Technical Bulletin Reprints, Vol. 3, pp. 82-84. College Station, TX: Stata Press.

Sherwood, A. (1997). The impact of electronic trading on regulatory surveillance. *Journal of Financial Regulation and Compliance*, Vol. 5 No. 4, pp. 299-305.

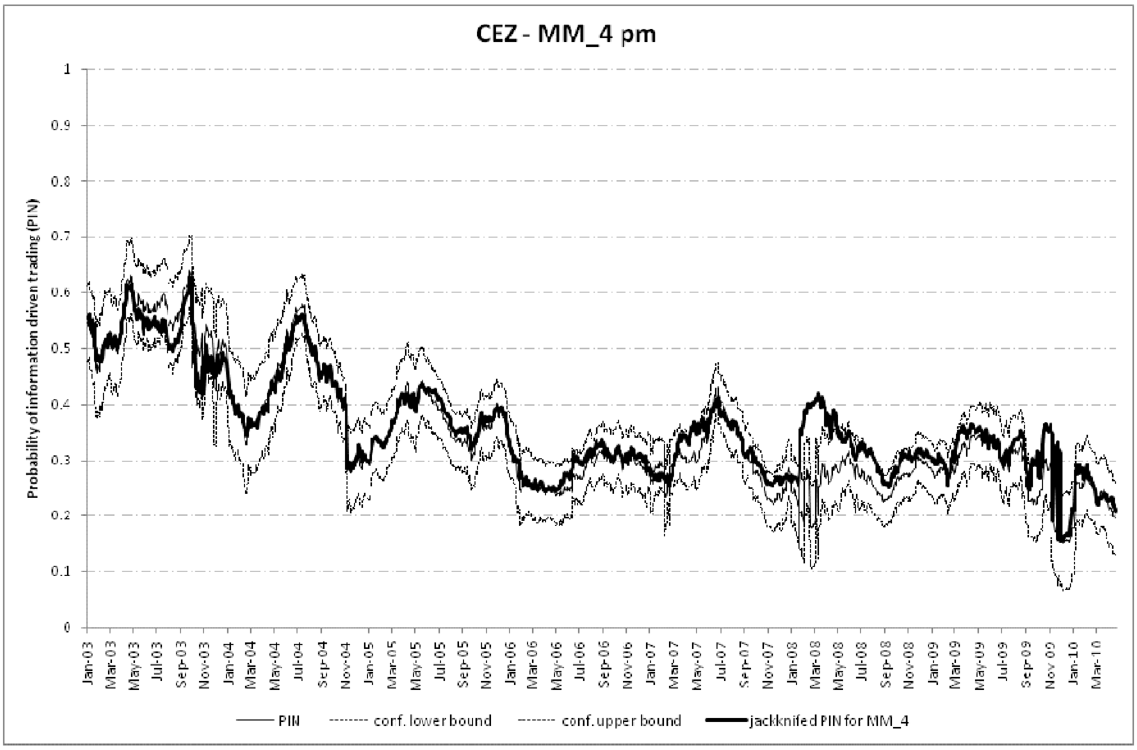
Sarkar, A. (1995). Dual trading: winners, losers and market impact. *Journal of Financial Intermediation,* Vol. 4 No. 1, pp. 77-93.

Vega, C. (2006). Stock price reaction to public and private information. *Journal of Financial Economics,* Vol. 82 No. 1, pp. 103-133.

Wang, A. and Chae, J. (2003). Who makes markets? Cross-sectional variation in voluntary liquidity provision. Working paper 4434-03, MIT Sloan School of Management, MIT, Cambridge, October.

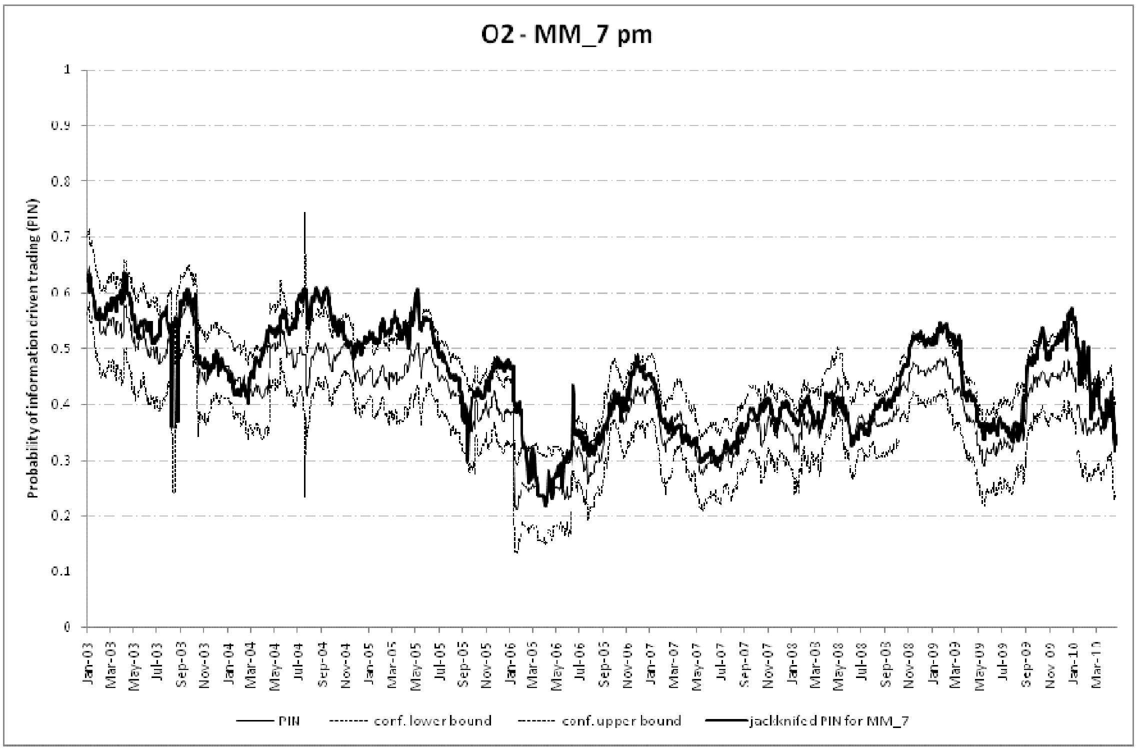
1.8 APPENDIX

Figure 1.2: Estimated PIMM for CEZ using a 90-day rolling window, afternoon trading



Note: The figure represents a graphical version of the test; suspicious behavior is identified when results for particular MMs (thick line) exceed the limits of the confidence interval.

Figure 1.3: Estimated PIMM for Telefonica O2 using a 90-day rolling window, afternoon trading



Note: The figure represents a graphical version of the test; suspicious behavior is identified when results for particular MMs (thick line) exceed the limits of the confidence interval.

Table 1.3a: Market capitalization and overall traded volumes

Stock	Year	Mkt. cap.	Turnover	SPAD trades	Sys. trades	APD	B/S	Price	Price change	MM
AAA	2007	3	22%	0.93	0.34	14.4	0.89	44.4	na	7
	2008	1	75%	0.94	0.61	13.2	0.82	9.1	-80%	7
	2009	1	13%	1.00	0.90	7.8	0.92	13.5	49%	6
CME	2005	43	14%	0.81	0.56	18.3	1.30	1,409	18%	6
	2006	50	50%	0.96	0.64	42.2	1.05	1,462	4%	6
	2007	72	44%	0.99	0.68	44.3	1.12	2,106	44%	6
	2008	14	130%	0.98	0.52	29.0	0.85	382	-82%	6
	2009	25	69%	0.99	0.60	71.0	0.99	446	17%	6
CEZ	2003	86	51%	0.64	0.31	18.4	1.10	146	58%	10
	2004	202	54%	0.73	0.42	42.0	1.30	341	134%	9
	2005	436	69%	0.68	0.45	124.5	1.00	736	116%	10
	2006	569	61%	0.94	0.48	157.8	0.96	960	30%	9
	2007	807	50%	0.98	0.44	119.1	1.02	1,362	42%	9
	2008	465	83%	0.99	0.44	110.9	0.93	785	-42%	9
	2009	465	44%	1.00	0.41	66.5	0.99	864	10%	9
CRA	2003	11	45%	0.72	0.25	5.3	2.00	345	83%	8
	2004	14	67%	0.61	0.29	9.8	1.10	444	29%	8
ECM	2006	5	50%	0.99	0.53	84.4	1.51	1,432	na	6
	2007	5	351%	0.99	0.60	44.7	0.95	1,203	-16%	6
	2008	2	285%	0.98	0.51	25.0	0.61	261	-78%	7
	2009	2	26%	0.98	0.80	8.2	1.05	308	18%	7
EB	2003	191	7%	0.78	0.61	17.4	1.20	798	59%	6
	2004	287	11%	0.85	0.63	31.6	1.20	1,187	49%	6
	2005	334	14%	0.83	0.63	43.5	1.00	1,372	16%	8
	2006	505	12%	0.94	0.66	54.0	1.05	1,601	17%	9
	2007	411	25%	0.99	0.71	92.5	0.94	1,301	-19%	9
	2008	133	68%	1.00	0.65	114.6	0.94	419	-68%	9
	2009	264	22%	0.99	0.62	100.4	1.01	699	67%	9
KB	2003	92	110%	0.65	0.40	38.0	1.00	2,418	16%	9
	2004	124	120%	0.60	0.34	61.1	1.00	3,272	35%	9
	2005	131	158%	0.64	0.43	95.1	0.90	3,441	5%	10
	2006	118	90%	0.94	0.57	68.8	0.92	3,099	-10%	9
	2007	166	82%	0.99	0.57	76.2	1.13	4,371	41%	8
	2008	113	102%	0.99	0.59	100.7	0.97	2,970	-32%	7
	2009	149	42%	0.99	0.50	74.3	1.06	3,929	32%	6

Note: Mkt. cap. is market capitalization in billions of CZK at the end of the year; Turnover is the turnover ratio during the year as a percentage of Mkt. cap.; SPAD trades is the ratio of the SPAD traded volume on overall traded volume; Sys. Trades is the ratio of system trades (usually classic trades with an identification of the market maker) to the overall traded volume; APD is the average number of trades during a trading day; B/S is the buy over sells ratio; Price is the price at the end of the year; Price change is the percentage change of the price during the year; MM is the id number of the market maker.
Source: PSE fact books, www.akcie.cz and authors' computations.

Table 1.3b: Market capitalization and overall traded volumes

Stock	Year	Mkt. cap.	Turnover	SPAD trades	Sys. trades	APD	B/S	Price	Price change	MM
NWR	2008	19	229%	1.00	0.59	101.1	0.90	73	na	7
	2009	43	64%	0.99	0.65	87.2	1.02	162	120%	7
O2	2003	94	69%	0.49	0.17	22.5	1.20	291	19%	10
	2004	119	102%	0.52	0.16	35.9	1.20	369	27%	9
	2005	169	171%	0.44	0.14	43.0	1.00	525	42%	10
	2006	153	64%	0.88	0.41	62.8	0.92	476	-9%	10
	2007	175	58%	0.99	0.40	51.4	1.13	545	14%	10
	2008	137	68%	0.99	0.38	52.3	0.91	424	-22%	10
	2009	135	49%	0.99	0.40	38.6	1.01	418	-1%	10
ORCO	2005	na	na	0.78	0.61	18.8	1.10	1,809	41%	6
	2006	22	125%	0.96	0.76	65.1	1.09	2,755	52%	6
	2007	23	159%	0.99	0.64	54.9	0.87	2,165	-21%	8
	2008	2	630%	1.00	0.64	52.5	0.79	173	-92%	8
	2009	2	109%	1.00	0.74	34.0	1.06	170	-1%	8
PM	2003	30	64%	0.67	0.38	9.1	1.20	15,728	41%	9
	2004	32	91%	0.72	0.41	22.2	1.10	16,776	7%	8
	2005	35	101%	0.68	0.43	28.2	1.20	18,251	9%	8
	2006	21	89%	0.93	0.46	23.4	0.92	10,840	-41%	7
	2007	15	62%	0.99	0.47	16.0	1.08	7,933	-27%	7
	2008	12	42%	0.94	0.38	10.1	0.92	6,026	-24%	7
	2009	17	30%	0.94	0.39	9.1	1.03	8,796	46%	7
PEGAS	2006	7	48%	0.99	0.35	93.3	0.91	753	na	7
	2007	7	231%	0.95	0.48	35.0	0.93	751	0%	8
	2008	2	237%	0.97	0.57	21.9	0.78	233	-69%	8
	2009	4	71%	0.95	0.51	12.0	1.19	445	91%	8
UNI	2003	12	72%	0.60	0.34	8.2	1.30	66	92%	8
	2004	18	79%	0.68	0.35	9.5	1.00	98	48%	8
	2005	42	122%	0.78	0.54	45.1	1.00	233	138%	8
	2006	42	114%	0.95	0.59	47.2	1.01	234	0%	6
	2007	61	75%	0.88	0.55	33.3	1.05	338	44%	7
	2008	27	105%	0.98	0.60	28.0	0.90	150	-56%	7
	2009	25	54%	0.98	0.53	17.7	1.11	140	-7%	7
VIG	2008	83	2%	1.00	0.76	11.6	0.84	646	na	5
	2009	121	1%	1.00	0.79	8.3	0.98	942	46%	5
ZEN	2004	29	59%	0.65	0.30	17.0	1.10	758	50%	8
	2005	43	232%	0.61	0.38	48.5	1.00	1,136	50%	8
	2006	48	222%	0.94	0.60	71.7	1.01	1,268	12%	9
	2007	37	300%	0.99	0.54	71.5	1.00	972	-23%	9
	2008	41	116%	0.92	0.33	28.5	1.09	1,078	11%	9

Table 1.4: Market share of market makers on the PSE during the sample period

Stock	AAA	CME	CEZ	CRA	ECM	EB	KB	O2	ORCO	NWR	PM	PN	UNI	VIG	ZEN
MM 1	**13%**	**24%**	**13%**	**12%**	**19%**	**16%**	**17%**	**11%**	**19%**	**20%**	**14%**	**17%**	**19%**	**28%**	**15%**
	599	14544	21891	297	3517	20258	24664	8952	9763	9262	4478	2750	9612	1462	8726
MM 2	**6%**	**12%**	**9%**	**8%**	**0%**	**9%**	**2%**	**7%**	**2%**	**3%**	**10%**	**11%**	**11%**		**8%**
	222	6271	15131	199	114	12052	1985	5948	1070	1883	3389	2057	5382		4903
MM 3			**0%**	**2%**			**0%**	**0%**			**1%**		**0%**		
			205	46			422	364			113		112		
MM 4	**9%**	**14%**	**13%**	**14%**	**17%**	**12%**	**14%**	**13%**	**16%**	**13%**	**13%**	**14%**	**16%**	**19%**	**14%**
	555	7745	20703	355	3455	15005	20066	10307	8687	6285	4248	2514	7813	1092	8064
MM 5	**26%**	**15%**	**9%**	**14%**	**15%**	**15%**	**12%**	**11%**	**17%**	**19%**	**13%**	**12%**	**18%**	**15%**	**9%**
	2447	10821	16578	348	4220	20477	17868	9607	12779	11915	4308	2483	9215	848	5618
MM 6	**10%**	**0%**	**10%**	**7%**	**17%**	**7%**	**12%**	**9%**	**2%**	**9%**	**11%**	**6%**	**5%**		**10%**
	483	84	17367	169	2894	9427	17371	7173	1441	3747	3618	1351	2326		5943
MM 7	**30%**	**19%**	**20%**	**16%**	**17%**	**16%**	**16%**	**25%**	**17%**	**25%**	**18%**	**19%**	**16%**	**21%**	**15%**
	2017	12894	32078	423	4136	21734	24112	20021	12033	13958	6263	3711	8606	1207	8878
MM 8			**0%**				**1%**	**3%**							
			885				857	2243							
MM 9			**7%**	**10%**		**7%**	**8%**	**6%**	**12%**	**1%**	**5%**	**10%**	**2%**		**10%**
			12865	258		8537	10280	4722	5125	354	1240	1659	1025		6024
MM 10	**7%**	**14%**	**13%**	**18%**	**15%**	**13%**	**14%**	**13%**	**15%**	**11%**	**14%**		**13%**	**17%**	**13%**
	267	7500	22088	475	2904	15859	20736	10407	7142	5326	4473		6279	931	7908
MM 11			**6%**			**4%**	**4%**	**4%**							**5%**
			9960			4187	4884	3097							2916

Note: Each row consists of the percentage of volume traded through mandatory trades and the number of mandatory trades of a given market maker during the sample period 1 January 2003 to 30 August 2010. Source: www.akcie.cz and authors' computations.

Table 1.5: SPAD traded volume and percentage of block trades

Stock	Year	Volume bil. CZK	Block trades	SPAD with ID	SPAD no ID	SPAD ID no cross
AAA	07-10	1.1	**6%**	49%	45%	**42%**
CME	2005	5.9	**17%**	55%	26%	**52%**
CME	06-10	98.8	**2%**	62%	36%	**57%**
CEZ	03-05	445.6	**30%**	42%	27%	**40%**
CEZ	06-10	1343.3	**2%**	45%	53%	**42%**
CRA	03-05	14.2	**32%**	25%	41%	**23%**
ECM	06-10	24.0	**1%**	58%	41%	**53%**
EB	03-05	91.4	**16%**	62%	20%	**59%**
EB	06-10	318.7	**1%**	67%	32%	**62%**
KB	03-05	448.6	**37%**	39%	24%	**36%**
KB	06-10	445.9	**2%**	56%	42%	**52%**
NWR	08-10	89.5	**0%**	62%	37%	**54%**
O2	03-05	472.4	**53%**	14%	32%	**13%**
O2	06-10	365.1	**4%**	40%	56%	**37%**
ORCO	2005	5.6	**20%**	60%	19%	**56%**
ORCO	06-10	74.6	**2%**	68%	30%	**63%**
PM	03-05	82.7	**30%**	39%	30%	**36%**
PM	06-10	38.9	**5%**	44%	51%	**41%**
PEGAS	06-10	25.3	**4%**	48%	47%	**44%**
UNI	03-05	70.9	**22%**	45%	31%	**41%**
UNI	06-10	133.9	**6%**	56%	37%	**52%**
VIG	08-10	3.3	**0%**	76%	23%	**69%**
ZEN	03-05	119.9	**39%**	35%	25%	**33%**
ZEN	06-09	260.5	**4%**	53%	43%	**50%**

Note: Volume is the traded volume on SPAD; Block trades is the percentage of the SPAD volume; SPAD with ID (no ID) is the percentage of SPAD traded volume with (without) an identification of the market maker; SPAD ID no cross is the percentage of SPAD traded volume analyzed in our study (standard SPAD trades through the market maker).
Source: www.akcie.cz and authors' computations.

Table 1.6: Changes in the trading lot size

Stock	Time period	LOT size	Price (CZK)		Volume mil. CZK	
			Min	Max	Min	Max
AAA	Sep 07–Aug 10	**3,000**	4.8	56.5	0.01	0.17
CME	Jun 05–Aug 10	**1,000**	104	2317	0.10	2.32
CEZ	Jan 03–Oct 04	**20,000**	87	282	1.74	5.63
	Oct 04–Aug 05	**10,000**	257	552	2.57	5.52
	Aug 05–Aug 10	**5,000**	523	1435	2.61	7.18
CRA	Jan 03–Sep 04	**3,000**	180	535	0.54	1.61
ECM	Dec 06–Aug 10	**500**	120	2065	0.06	1.03
EB	Jan 03–Sep 03	**500**	1850	2975	0.93	1.49
	Sep 03–Mar 04	**1,000**	2685	3886	2.69	3.89
	Mar 04–Jul 04	**500**	3530	4236	1.77	2.12
	Jul 04–Aug 10	**2,000***	196.1*	1743*	0.39	3.49
KB	Jan 03–Sep 03	**2,000**	1817	2680	3.63	5.36
	Sep 03–Jun 08	**1,000**	2210	4540	2.21	4.54
	Jun 08–Aug 10	**500**	1520	4295	0.76	2.15
O2	Jan 03–Aug 10	**5,000**	240	628	1.20	3.14
NWR	May 08–Aug 10	**5,000**	59	624	0.30	3.12
ORCO	Feb 05–Aug 10	**500**	70	3785	0.04	1.89
PM	Jan 03–Mar 04	**200**	10400	20740	2.08	4.15
	Mar 04–Aug 10	**100**	3650	21451	0.37	2.15
PEGAS	Dec 06–Aug 10	**1,000**	166	848	0.17	0.85
UNI	Jan 03–Feb 05	**20,000**	34	181	0.68	3.63
	Feb 05–Aug 10	**10,000**	89	346	0.89	3.46
VIG	Feb 08–Aug 10	**500**	400	1478	0.20	0.74
ZEN	Jun 04–Jun 07	**3,000**	480	1571	1.44	4.71
	Jun 07–Apr 09	**2,000**	784	1448	1.57	2.90

Note: LOT is the number of shares in the trading lot; Price and Volume Min (Max) is the minimum (maximum) price and volume in CZK during the corresponding time period. * indicates stock splitting.
Source: www.akcie.cz and authors' computations.

Table 1.7a: Extent of information-driven trading originating from the behavior of informed market makers

Stock	Time period	morning/ afternoon	PIN	PIMM	Diff	T-stat	P-value
CME (MM1)	21.2.2009-4.9.2009	aft	**0.263** (0.029)	**0.352** (0.029)	**0.088** (0.036)	2.46	0.014
CEZ (MM7)	1.4.2009-1.10.2009	morn	**0.253** (0.028)	**0.336** (0.031)	**0.083** (0.036)	2.28	0.022
CEZ (MM4)	1.2.2008-1.7.2008	aft	**0.176** (0.040)	**0.368** (0.029)	**0.193** (0.052)	3.69	0.000
CEZ (MM7)	1.9.2009-9.2.2010	aft	**0.239** (0.037)	**0.338** (0.036)	**0.100** (0.041)	2.43	0.015
CRA (MM4)	26.6.2003-15.10.2003	aft	**0.550** (0.109)	**0.784** (0.088)	**0.234** (0.117)	2.00	0.045
EB (MM1)	25.5.2004-1.11.2004	morn	**0.344** (0.035)	**0.248** (0.038)	**0.097** (0.044)	2.22	0.027
EB (MM1)	1.11.2008-16.5.2009	morn	**0.268** (0.027)	**0.301** (0.028)	**0.033** (0.014)	2.35	0.019
EB (MM7)	1.3.2008-9.9.2008	morn	**0.300** (0.024)	**0.346** (0.025)	**0.046** (0.022)	2.06	0.039
KB (MM7)	5.2.2003-7.7.2003	aft	**0.570** (0.036)	**0.642** (0.034)	**0.072** (0.022)	3.30	0.001
KB (MM7)	2.9.2005-26.1.2006	aft	**0.362** (0.037)	**0.461** (0.036)	**0.100** (0.040)	2.48	0.013
NWR (MM1)	1.7.2008-18.11.2008	aft	**0.301** (0.028)	**0.371** (0.030)	**0.069** (0.018)	3.79	0.000
ORCO (MM5)	5.8.2009-3.12.2009	morn	**0.399** (0.049)	**0.507** (0.043)	**0.107** (0.031)	3.43	0.001
ORCO (MM7)	21.2.2010-21.6.2010	morn	**0.407** (0.058)	**0.584** (0.057)	**0.177** (0.061)	2.90	0.004
ORCO (MM1)	3.3.2009-5.8.2009	aft	**0.466** (0.047)	**0.598** (0.037)	**0.132** (0.041)	3.22	0.001
ORCO (MM7)	1.11.2009-22.4.2010	aft	**0.510** (0.049)	**0.586** (0.051)	**0.076** (0.037)	2.07	0.038

Note: PIMM is the estimate of information-driven trading using the sum of buys and sells excluding the buys and sells of a given market maker. Standard errors are in parentheses.
Source: authors' computations.

Table 1.7b: Extent of information-driven trading originating from the behavior of informed market makers

Stock	Time period	morning/ afternoon	PIN	PIMM	Diff	T-stat	P-value
PM (MM7)	1.9.2009-11.2.2010	morn	**0.611** (0.059)	**0.754** (0.046)	**0.143** (0.056)	2.55	0.011
PM (MM7)	21.7.2004-29.11.2004	aft	**0.459** (0.048)	**0.562** (0.047)	**0.103** (0.043)	2.40	0.016
PM (MM7)	11.9.2007-22.2.2008	aft	**0.415** (0.058)	**0.541** (0.056)	**0.127** (0.063)	2.01	0.045
PM (MM2)	1.10.2007-22.2.2008	aft	**0.418** (0.057)	**0.531** (0.057)	**0.113** (0.036)	3.10	0.002
O2 (MM7)	21.5.2004-31.8.2004	morn	**0.485** (0.050)	**0.638** (0.043)	**0.152** (0.044)	3.50	0.000
O2 (MM7)	18.5.2005-29.9.2005	morn	**0.527** (0.045)	**0.658** (0.036)	**0.131** (0.034)	3.89	0.000
O2 (MM7)	1.12.2006-10.4.2007	morn	**0.380** (0.036)	**0.459** (0.037)	**0.080** (0.030)	2.63	0.008
O2 (MM7)	9.10.2009-27.2.2010	morn	**0.434** (0.043)	**0.528** (0.048)	**0.095** (0.034)	2.79	0.005
O2 (MM7)	11.6.2004-27.12.2004	aft	**0.466** (0.036)	**0.570** (0.034)	**0.103** (0.034)	3.02	0.003
O2 (MM7)	21.12.2005-16.5.2006	aft	**0.390** (0.033)	**0.472** (0.038)	**0.082** (0.034)	2.38	0.017
O2 (MM7)	21.1.2009-29.6.2009	aft	**0.438** (0.033)	**0.510** (0.034)	**0.072** (0.035)	2.09	0.037
O2 (MM7)	1.1.2010-12.5.2010	aft	**0.449** (0.046)	**0.556** (0.048)	**0.107** (0.053)	2.03	0.043
O2 (MM10)	14.2.2010-21.7.2010	aft	**0.344** (0.047)	**0.485** (0.045)	**0.141** (0.071)	2.00	0.046
AAA (MM7)	17.5.2009-23.11.2009	morn	**0.464** (0.066)	**0.652** (0.071)	**0.188** (0.081)	2.32	0.020
AAA (MM7)	1.11.2008-22.4.2009	aft	**0.572** (0.073)	**0.682** (0.076)	**0.109** (0.053)	2.06	0.039

Note: PIMM is the estimate of information-driven trading using the sum of buys and sells except the buys and sells of a given market maker. Standard errors are in parentheses.
Source: authors' computations.

Table 1.8: Extent of information-driven trading before and after changing the lot size

Stock	Date	LOT 1	LOT 2	morn/ aft	PIN 1	PIN 2	Diff	T-stat	P-value
CEZ	15.10.2004	20,000	10,000	morn	**0.462** (0.038)	**0.352** (0.030)	**0.110** (0.072)	1.52	0.128
				aft	**0.517** (0.042)	**0.416** (0.032)	**0.101** (0.065)	1.55	0.120
CEZ	12.8.2005	10,000	5,000	morn	**0.333** (0.027)	**0.232** (0.030)	**0.101** (0.045)	2.24	0.025
				aft	**0.428** (0.041)	**0.332** (0.030)	**0.096** (0.065)	1.48	0.139
EB	19.9.2003	500	1,000	morn	**0.376** (0.043)	**0.349** (0.037)	**0.027** (0.057)	0.47	0.636
				aft	**0.500** (0.061)	**0.521** (0.048)	**-0.021** (0.084)	0.25	0.802
EB	12.3.2004	1,000	500	morn	**0.384** (0.037)	**0.362** (0.035)	**0.022** (0.066)	0.33	0.744
				aft	**0.538** (0.047)	**0.434** (0.043)	**0.104** (0.080)	1.29	0.197
KB	5.9.2003	2,000	1,000	morn	**0.523** (0.030)	**0.352** (0.032)	**0.171** (0.057)	3.02	0.003
				aft	**0.575** (0.036)	**0.446** (0.034)	**0.130** (0.066)	1.95	0.051
KB	30.6.2008	1,000	500	morn	**0.310** (0.031)	**0.281** (0.027)	**0.029** (0.036)	0.80	0.426
				aft	**0.367** (0.038)	**0.266** (0.030)	**0.100** (0.056)	1.79	0.073
PM	12.3.2004	200	100	morn	**0.741** (0.040)	**0.498** (0.037)	**0.243** (0.091)	2.68	0.007
				aft	**0.713** (0.047)	**0.489** (0.047)	**0.225** (0.070)	3.20	0.001
UNI	24.2.2005	20,000	10,000	morn	**0.476** (0.050)	**0.334** (0.050)	**0.142** (0.064)	2.23	0.025
				aft	**0.380** (0.060)	**0.278** (0.059)	**0.102** (0.070)	1.45	0.148
ZEN	29.6.2007	3,000	2,000	morn	**0.287** (0.032)	**0.278** (0.044)	**0.009** (0.043)	0.21	0.837
				aft	**0.299** (0.037)	**0.144** (0.061)	**0.154** (0.080)	1.93	0.054

Note: The table shows the extent of information-driven trading within 90 trading days before and after a change in the lot size. Standard errors are in parentheses.
Source: authors' computations.

Chapter 2

In Brokers We Trust: Investment Recommendations and Stock Price Movements

Jan Hanousek and František Kopřiva*

CERGE-EI †

Abstract

We analyze the potential conflict of interest between analysts and associated brokers. In contrast to the existing literature we do not analyze prediction accuracy and/or biases in analyst recommendations. Instead, we focus our analysis on brokers and examine whether their behavior systematically differs before and after investment recommendations are released. The evolution and dynamics of brokers' quotes and trades are used to test for systematic trading patterns around the release of one's own investment recommendation. In the model we control for brokers' responses to other investment advice and employ a SUR estimation framework. Data from the Prague Stock Exchange are used to demonstrate our methodology. We find significant and systematic differences in brokers' behavior and conclude that misuse of investment recommendations is widespread.

JEL Classification: G14, G15, P34
Keywords: dealers' market, emerging markets, informed trading, investment recommendations, trading systems.

* Email addresses: jan.hanousek@cerge-ei.cz and frantisek.kopriva@cerge-ei.cz.
Address: CERGE-EI, P.O. Box 882, Politických vězňů 7, Prague 1, 111 21, Czech Republic.
The authors would like to thank Eva Hromádková, Štěpán Jurajda, Evžen Kočenda and Petr Zemčík for helpful comments. Earlier versions of this paper were presented at CERGE-EI, UPENN, and various conferences including MME and CES; we acknowledge comments by presentation participants. The research for this study was supported by a GAČR grant (403/11/0020). The views expressed are those of the authors and do not necessarily reflect the position of any of the affiliated institutions.
All errors remaining in this text are the responsibility of the author(s).
† A joint workplace of the Center for Economic Research and Graduate Education, Charles University, and the Economics Institute of the Academy of Sciences of the Czech Republic.

2.1 INTRODUCTION

The integration of brokerage and analytical services on a stock market creates conditions for a particular type of conflict of interest. This conflict of interest can manifest itself in two ways: First, analysts may have an incentive to issue biased recommendations; second, even if investment advice is unbiased, associated brokers may possess this information well before the other market participants and use it to their advantage (e.g. when associated brokers trade against a future recommendation in advance, the investment recommendation itself then has a significant effect on the market price).[1] While the vast majority of theoretical and empirical research on investment recommendations focuses on the first issue, i.e., analyst behavior, in this study we explore the second mechanism using publicly available high-frequency data. We treat the recommendation of a particular analyst as new information that affects the decision-making of all market participants. Associated brokers, however, may have access to this information before it is released to the public and may thus possess an informational advantage over the rest of the market. The primary goal of our paper is to detect the misuse of this advantage by analyzing brokers' trading behavior prior to and after the investment recommendation is issued, with a particular emphasis on their responses to their own recommendations. If there is no conflict of interest, we should see no systematic trading patterns a few trading days before or after an associated analyst issues a recommendation.

Contrary to the existing literature, we do not perform our analysis on restricted-access regulatory data, but on publicly available high-frequency data from trading platforms. In this way, we not only introduce a new approach to the analysis of investment recommendations but also overcome the problem of missing data, as the

[1] An increasing number of studies suggest that investors respond to investment recommendations and therefore imply the need for regulatory protection to avoid price manipulation and market abuse; see for example Womack (1996), Barber et al. (2007), Irvine et al. (2007), Asquith et al. (2005), and Li (2005). According to Morgan and Stocken (2003), analysts use upward-biased recommendations to increase the trading volume and therefore the trading fees. Agrawal and Chen (2008) use stock inventories; their results indicate that dealers facing a conflict of interest tend to issue more optimistic recommendations. The significance of these problems is further supported by several steps taken by legal and supervisory bodies on developed markets, e.g., the well-known investigation initiated by New York State Attorney General Eliot Spitzer that resulted in a settlement with ten Wall Street firms in December 2002 (SEC, 2002).

evolution of quotes and trades should easily replace the (often missing) regulatory information on stock inventories, portfolio structure, and proprietary trading profits. Moreover, publicly available data contain information that is available to the retail sector investor if he decides to enter a particular capital market, reflecting a wide range of expectations about future development including expert opinions and investment recommendations. Therefore, we might expect some reaction among the market participants to distributed market analyses. Less-informed retail sector investors may be especially sensitive to this information and thus follow these recommendations more closely. Further, our high-frequency data consist of trades and quotes that capture most of the interaction of large brokerage firms with the retail sector. Our study thus can better capture the misuse of the informational advantage of large participants in the market through transactions with the retail market. We demonstrate our approach on data from the Prague Stock Exchange trading platform for the period 2003–2008, which we match with a set of related investment recommendations. To date, this is the only study analyzing the conflict of interest stemming from brokers' investment recommendations that does not use regulatory data and the first such study in the context of Central European emerging markets.

The paper is organized as follows. The next section provides a short overview of investment recommendations in the context of an emerging market, with a particular emphasis on the market structure of the Prague Stock Exchange. Section 2.3 introduces the methodology, and a description of the data is given in Section 2.4. The results are presented in Section 2.5. Section 2.6 concludes.

2.2 Effect of Investment Recommendations and Emerging Markets

Most research analyzing the effects of investment recommendations has been conducted on data from developed capital markets such as that in the U.S., where regulation is quite strict and requires a separation of brokerage and investment banking activities.[2] It

[2] Several U.S. studies, however, do not support further regulation of investment recommendations as they argue that investors are aware of the possible conflict of interest and discount biased investment recommendations (see Fisch, 2006 and Agrawal and Chen, 2008). Recently, the unbiased and information value given in these recommendations has been discussed (e.g., Bhattacharya et al., 2012) as well as its overall influence (e.g., Loh and Stulz, 2011). In addition, some of the existing U.S. capital market

is therefore not surprising that the results of these studies generally do not support the hypothesis that investors are systematically misled by investment recommendations. It would be a mistake, however, to extend these findings to emerging markets, for several reasons: (1) Emerging capital markets are typically not subject to a high level of regulation;[3] (2) due to the smaller size of emerging markets, brokers have strong market power and substantial latitude for price manipulation; (3) small investors are inexperienced and unaware of a possible conflict of interest. In addition, Girard and Biswas (2007) show that compared to developed markets, emerging markets exhibit greater sensitivity to the unusual volumes associated with the release of new information such as investment recommendations. Moreover, control over large market participants is usually limited, as the regulatory authority often does not collect data on proprietary trading, broker inventories, etc. Overall, the problem of the misuse of investment recommendations and price manipulation could be more severe in emerging markets.

Existing literature on the effect of investment recommendations in the context of emerging markets is very limited and, likely due to the lack of regulatory data, tend to analyze interactions between analyst recommendations and price change. Moshirian, Ng, and Wu (2009), in their sample of 13 emerging countries, show that stock prices react strongly to stock analyst recommendations. They also report a stronger positive bias in analyst recommendations and revisions in emerging markets than in developed markets. Similarly, Kiymaz (2002) analyzed the effects of stock market rumors related to information release at the Istanbul Stock Exchange. He found that positive and significant abnormal returns are observed in the days prior to the publication date and that negative yet insignificant returns are observed in the post-publication period. This supports our view of emerging markets, especially the possible existence of information leak and/or strategic trading around the time when recommendations are released.

Even in developed markets, however, interaction between institutional trading and released recommendations is observed. Irvine et al. (2007), for example, analyzed the behavior of institutional traders immediately before the release of analysts' initial

---

regulations are criticized for being too restrictive and likely to reduce the quality and quantity of information available to retail investors (Fisch, 2006).

[3] See e.g., Hanousek and Filer (2002) or Torre, Gozzi, and Schmukler (2007).

buy recommendations. They find very high institutional trading volume and buying beginning five days before buy recommendations are publicly released and typically before the trading based on such recommendations earns an abnormal profit. Therefore in our analysis we consider five- and ten-day windows around the release of each recommendation.

Even on regulated markets a relationship exists between associated analysts' recommendations. Kadan et al. (2009), for instance, demonstrate that affiliated analysts are still reluctant to issue pessimistic recommendations, while other literature consistently shows that analysts tend to over-recommend buying the stocks of firms with which they are affiliated (Lin and McNichols, 1998; Michaely and Womack, 1999; Barber and Trueman, 2007). This can be explained by the desire of analysts to generate trading commissions, which is supported by the findings of Ertimur et al. (2007) who show a correlation between the type of recommendation, profitability, the accuracy of forecasts, and conflict of interest arising from banking activity.

In this study we use data from the Prague Stock Exchange (PSE) to demonstrate our methodology. The PSE represents a typical electronic dealers' market, in which market makers play a dominant role in affecting the price for a short time interval as well as for a longer period (see Hanousek and Kopriva, 2011). Although capital market regulation has improved in line with EU legislation, differences between the regulation of the Czech capital market and the regulation of a developed market such as the NYSE or the LSE are still significant.[4] Brokers on the Czech capital market have enough market power to influence stock prices for a short time period and, similar to other emerging markets, they can be involved in dual trading – the practice of submitting customer orders and simultaneously trading as dealers on their own account. Further, the lack of regulation of investment recommendations, as well as no requirement for the separation of brokerage and investment banking activities, implies that the Czech Republic still has many features that exacerbate problems related to investment recommendations.

---

[4] While the Prague Stock Exchange started operation in 1993, the Czech Securities Commission commenced operation in April 1998. The role of the Czech Securities Commission was to strengthen investor and investment instruments issuer trust in the capital market. As of April 2006 the Czech National Bank took over the activities of the Czech Securities Commission, which at that point ceased to exist.

2.3 METHODOLOGY – USING STOCK QUOTES TO ANALYZE BROKERS' BEHAVIOR

Our aim is to capture and analyze brokers' trading behavior, focusing on the dates around which associated analysts issue investment recommendations. Recently, several trading platforms have enabled participants to see real time quotes/positions of each active broker/market maker, meaning there exist high-frequency trading data for each broker.[5]

In general, brokers' trading positions are well-described by their buy/sell statistics and by their positions on the bid and ask sides. In our analysis, we omit all cross trades, mainly because of their different nature (for example, some are used to set up standard operations such as the leveraged trading of a broker's client) and we consider only mandatory trades.[6] For capturing and summarizing a broker's position on a bid or ask we use the relative distance from the best quotes and average the rank on the bid or ask. Since the original trading data are collected at a high frequency, for daily versions we need to compute the time-weighted averages of these variables.

Methodologically, in our analysis we follow three key steps: (1) Construct statistics that summarize the daily behavior of a given broker from publicly available high-frequency data; (2) use these statistics as dependent variables in seemingly unrelated regressions (SUR) with information about the timing and direction of investment recommendations used as a regressor; (3) assess the differences in trading behavior of brokers before and after their own recommendations as well as the differences in reacting to one's own as opposed to external recommendations.

In the first step, we summarize brokers' trading behavior at a daily frequency in the following variables (computed for each share):

a) $Buy_{j,t}$ = total number of mandatory buys (in lots) by each broker j on trading day t.

b) $Sell_{j,t}$ = total number of mandatory sells (in lots) by each broker j on trading day t.

c) Time-weighted percentage difference from the best bid, computed for broker j on trading day t:

---

[5] The availability of such data varies across markets and trading platforms.

[6] By mandatory trades we mean buy (sell) operations when the broker has the best offer on the ask (bid) side.

First, we compute the percentage difference of every bid that broker j makes on trading day t from the corresponding best bid as

$$BBDf_{j,time} = \frac{|Bid_{j,time} - BestBid_{time}|}{BestBid_{time}} * 100 \quad . \tag{2.1}$$

We then weight it by the time interval for which this distance holds during the trading day; i.e. the final daily statistics is the time-weighted average of (2.1) collapsed to daily frequency.

d) Time-weighted percentage difference from the best ask, computed for each broker j on trading day t:

$$BADf_{j,time} = \frac{|Ask_{j,time} - BestAsk_{time}|}{BestAsk_{time}} * 100 \quad . \tag{2.2}$$

As in c) we collapse intra-day data to the daily level using time-weights representing the duration of a particular position in (2.2).

Analogously, for robustness we also consider the average ranks of the bid and ask.

e) Time-weighted daily average rank on the bid of broker j, where we compute the rank of broker j on the bid side at a particular time, and then again weight it by the time interval for which this rank holds. As for the other statistics, the final value is the time-weighted average rank of broker j, representing his average position on the bid during the trading day.

f) Time-weighted daily average rank on the ask of broker j, the same as in e) but computed for ask positions.

The variables defined in a) through f) above not only reflect the trading behavior of a particular broker but also allow for comparison with the behavior of other brokers. We are not only interested in the change of behavior of an individual broker before and after a particular recommendation is issued, but also in whether his change of behavior is notably different from the behavior of other brokers on the market.

Since we know the exact timing of each recommendation, we can link them with brokers' trading behavior and analyze the differences around the releases of the recommendations. The reaction to a particular recommendation differs depending on whether it is a positive (BUY) or negative (SELL) recommendation and on how the particular recommendation compares with the previous recommendation. Therefore, for each broker we define several 0/1 indicators (dummy variables) defining a neighborhood of *k* trading days before and after the release of the recommendation by associated analysts. The choice of *k* trading days allows us to see whether there is a reaction and, if so, how long it lasts (as a baseline we use k = 5 and 10, but we also consider k = 15 and asymmetric windows for robustness checks).

Let us define for each broker *j* and recommendation type *r* the following 0/1 indicators (dummy variables):

$$\mathbf{B}^{\mathbf{r}}_{\mathrm{j,own}} = \begin{cases} 1 \text{ for } k \text{ trading days } \underline{\textit{before}} \text{ release of recommendation of } j^{\mathrm{th}} \text{ broker} \\ 0 \text{ otherwise} \end{cases}$$

$$\mathbf{A}^{\mathbf{r}}_{\mathrm{j,own}} = \begin{cases} 1 \text{ for } k \text{ trading days } \underline{\textit{after}} \text{ release of recommendation of } j^{\mathrm{th}} \text{ broker} \\ 0 \text{ otherwise} \end{cases}, \tag{2.3}$$

where *r* represents any possible recommendation: positive, negative, positive change, or negative change.[7]

Because each broker could react to any investment advice known to the market, we should also consider the effects of recommendations issued by other brokers. Therefore, as in (3.3) we define dummy variables capturing the neighborhoods of the recommendations released by other local brokers; *r* again stands for any type of recommendation:

$$\mathbf{B}^{\mathbf{r}}_{\mathrm{j,other}} = \begin{cases} 1 \text{ for } k \text{ trading days } \underline{\textit{before}} \text{ another broker's recommendation release} \\ 0 \text{ otherwise} \end{cases}$$

$$\mathbf{A}^{\mathbf{r}}_{\mathrm{j,other}} = \begin{cases} 1 \text{ for } k \text{ trading days } \underline{\textit{after}} \text{ another broker's recommendation release} \\ 0 \text{ otherwise} \end{cases}. \tag{2.4}$$

Finally, in order to capture the effect of recommendations coming from external financial analysts (i.e. analysts not associated with any brokers operating on the stock market), we define

$$\mathbf{B}^{\mathbf{r}}_{\mathrm{ext}} = \begin{cases} 1 \text{ for } k \text{ trading days } \underline{\textit{before}} \text{ release of external analyst's recommendation} \\ 0 \text{ otherwise} \end{cases} \tag{2.5}$$

[7] A positive change means a change from a negative (SELL) recommendation to a neutral (HOLD) or positive (BUY) recommendation. A negative change means a change from a positive (BUY) recommendation to a neutral (HOLD) or negative (SELL) recommendation.

$$\mathbf{A}^{\mathbf{r}}_{\text{ext}} = \begin{cases} 1 & \text{for } k \text{ trading days } \underline{\textit{after}} \text{ release of external analyst's recommendation} \\ 0 & \text{otherwise} \end{cases}.$$

To analyze the effect of investment recommendations on the trading behavior of broker *j* let us consider the following specification:

$$trading_{jt} = \eta_j + \sum_{\substack{r=type\,of\\ reccomendation}} \left[\beta_j \boldsymbol{B}^{r}_{j,own_t} + \alpha_j \boldsymbol{A}^{r}_{j,own_t} + \gamma_j \boldsymbol{B}^{r}_{j,other_t} + \delta_j \boldsymbol{A}^{r}_{j,other_t} + \varphi_j \boldsymbol{B}^{r}_{ext_t} + \phi_j \boldsymbol{A}^{r}_{ext_t}\right] + \varepsilon_j \qquad j = 1,\ldots,J, \qquad t = 1,\ldots,D, \tag{2.6}$$

where the variable *trading* stands for all trading proxies defined in a) through f), i.e. the number of buys and sells; the percentage difference from the best bid and ask; and the average rank of the bid and ask. As mentioned above, as baselines we use time windows of five and ten trading days. Therefore, the dummy variables $\boldsymbol{B}^{r}_{j,own}$, $\boldsymbol{B}^{r}_{j,other}$, and $\boldsymbol{B}^{r}_{ext}$ are equal to one for ten trading days <u>before</u> the particular recommendation has been released.[8] Similarly, $\boldsymbol{A}^{r}_{j,own}$, $\boldsymbol{A}^{r}_{j,other}$, and $\boldsymbol{A}^{r}_{ext}$ are equal to one for ten trading days <u>after</u> the particular recommendation was made public.

Subscript *j* is used to designate each broker, subscript *t* marks the trading day, and superscript *r* denotes the type of recommendation. η_j represents the mean of the analyzed trading variable for broker *j*. The coefficients α_j, β_j, γ_j, δ_j φ_j, and ϕ_j capture <u>systematic</u> effects before and after the release of recommendations made by each type of analyst. In particular, our main coefficients of interest β_j and α_j measure systematic shifts in the trading patterns of broker *j* before and after the release of investment recommendations issued by associated analysts. The other variables in specification (2.6) are included to filter a possible overlap in the timing of recommendations as well as to control for the reactions of broker *j* to other investment advice.

As specified in (2.6), we analyze the trading patterns by regressing each particular trading variable on a set of dummies representing the timing of all types of

---

[8] We keep the notation as it is above, where the subscript *own* is used when the broker posted the recommendation, the subscript *other* is used when at least one of the other brokers posted the recommendation, and the subscript *outside* is used when an external analyst posted the recommendation.

recommendation issued by all kinds of analyst. One potential problem, however, is that while the analysis of trading data could point to interactions between associated analysts and brokers, it might not detect which came first. If a broker's trading was primarily based on previous knowledge of an associated analyst's recommendation (more likely) or if the recommendation was released in order to maintain the broker's inventories (less likely), there could be an endogeneity problem related to the timing of the recommendation. If we could take the timing of the recommendation as given (that is, if it was decided by the analysts) then the right-hand-side dummy variables would be pre-determined and the estimated coefficients would be unbiased. Clearly, if the error term and explanatory variables are correlated then the estimation procedure would lead to biased coefficients. Nonetheless, we believe that our estimation provides consistent estimates. First, as indicated in the literature (e.g. Irvine et al., 2007) the analyst's recommendation takes some time and typically starts with a potential information leak. Second, we conducted estimation (2.6) over different time windows; the similarity of results shows there to be consistency of the estimated coefficients.

For estimating the empirical specification we employ a seemingly unrelated regression (SUR) setup, where for a given share we estimate equations for all brokers $j = 1,..,J$ together. This approach provides more efficient estimates of the parameters of interest by using cross-equation correlations caused by, e.g., common exogenous shocks affecting all brokers such as a change in market trends. Since we estimate specification (2.6) over the whole sample period, we control for interference between various recommendations (released at a similar time) and for heterogeneous shocks affecting the behavior of all brokers.

2.4 Data and Descriptive Statistics

For our analysis, we use information on all investment recommendations during the period 2003–2008, which are publicly available online at www.ipoint.cz, together with high-frequency data about broker activity on the SPAD trading system of the PSE, also publicly available online at www.akcie.cz.[9] In the analysis we only use data on blue chip stocks, i.e. shares from the top-tier trading segment.

The high-frequency trading data consists of all SPAD trades and all SPAD quotes with the identification of brokers/market makers for all stocks traded during the time span 10 February 2004 to 31 December 2008. The dataset of SPAD trades consists of the stock ID, date and time, number of shares traded, price, traded volume, type of trade, and indicator of a mandatory sell or buy (when the broker's quote was the best bid price or best sell price), including the identification of the broker. The dataset of SPAD quotes consists of the stock ID, date and time, bid and ask prices, bid and ask volumes, and identification of the broker.

Analysts in the Czech Republic produce most investment recommendations in the form of buy and sell recommendations together with target prices (one year ahead). Most publish their recommendations regularly, covering nearly all the blue chip stocks. As the wording of recommendations and their scales vary considerably, to simplify the analysis we merge recommendations into three main categories: sell, hold, and buy (negative, neutral, and positive in our terms). Even though the I/B/E/S[10] uses five categories ranging from strong sell to strong buy, given the actual structure of recommendations, three categories is more appropriate for model identification.

The dataset of investment recommendations consists of the date, identification of the stock, issuer of the recommendation, target price, and recommendation (buy, sell, or hold). For some recommendations an additional description of the previous recommendation of the same issuer is included. We dropped all investment recommendations before 10 February 2004 as we do not have any quote data for this time interval. This left us with 1317 investment recommendations for stocks traded in SPAD that contained information on the type of recommendation. We matched the recommendation to the standard scale: buy, hold and sell. Detailed information on the

---

[9] www.ipoint.cz is an internet site owned by CEKIA (Czech Capital Information Agency) that provides detailed monitoring of press releases, investment recommendations, and analyst views associated with the PSE. www.akcie.cz is an internet site offering high-frequency trading data in real time with a delay of 15 minutes.

[10] The Institutional Brokers Estimate System (I/B/E/S) is a unique service which monitors the earnings estimates of companies of interest to institutional investors.

basic characteristics of the shares studied, including the number of quotes and investment recommendations released, is presented in Table 2.1 (in the appendix). Further, we divided the investment recommendations by the type of issuer: 1) investment firms that also act as brokers on the PSE (11 firms); and 2) all other external investment analysts/firms who posted at least one investment recommendation during the analyzed time span.

Since the open phase of the SPAD system runs each trading day from 9:15 a.m. to 4:00 p.m. we include in the analysis only quotes and trades during this time interval. As described in the methodology section, we use high-frequency intra-day data on the quotes and trades of brokers to create a proposed battery of trading variables, namely the number of mandatory buys and sells during a trading day, to the time-weighted average from intra-day data about rank on the bid and ask side or the percentage difference from best quotes. We then match brokers' trading data with the dates and information on investment recommendations. For the sensitivity analysis, we analyze time windows running from 5 to 15 trading days around each recommendation; the main results will be presented for 5 and 10 trading-day windows.

2.5 RESULTS

The main goal of this study is to determine whether brokers on the stock market misuse the potential informational advantage stemming from their association with analysts. This misuse could manifest in behavior different from other market participants. Although individual patterns of significance and the direction of the coefficients for each stock and broker pair may be interesting from a regulatory point of view, we examine these patterns more comprehensively to get a broader view. During the studied period the PSE was generally on an upside trend, so we present here only the results for positive recommendations.

Table 2.2 (in the appendix) provides a general summary of the occurrence of all possible combinations of behavior before and after the release of recommendations by associated analysts, measured by the occurrence of positive/negative/insignificant coefficients for the respective dummy variables. The numbers are summarized over all broker-share pairs for six trading behavior proxies.[11] By interpreting the systematic patterns in Table 2.2, we can answer questions regarding the existence of informational advantage and how it was used.

1. *Is the timing of recommendations unknown to associated brokers?*

This question can be addressed by ascertaining whether the estimated coefficients $\hat{\beta}_j$ (i.e., a systematic shift before the release of one's own recommendations) are significantly different from zero. For the 10-day window we see significant coefficients in about 28% of the cases for rank positions, 32% of the buy/sell measures, and about 42% of the quotes. For the 5-day window the results are even stronger. We observe significant coefficients in about 30% of the cases for rank positions, 36% of the buy/sell measures and about 44% of the quotes.[12] The evidence thus suggests that brokers either know about the timing of the recommendation, or recommendations were issued upon their request. From the trading data we cannot distinguish the direction of the causality, but the significant coefficients before the release of recommendations indicate interactions between brokers and associated analysts. Let us note that the high number of cases (broker and share) where we see systematic non-zero responses before the release of one's own recommendation also indicates an information leak and can be used as an additional indicator of conflict of interest.

2. *Is broker trading behavior (around the time of the investment recommendation) consistent with the recommendation issued by associated brokers?*

In order to answer this question, we first analyze the expected signs of the estimated coefficients for positive recommendations.

- ***Ask difference*, *Ask rank*, and *Sell*.** If a positive recommendation resonates with a broker's view or if there is a positive effect of the recommendation in question, then we should expect the broker to be less active on the sell side, especially

[11] There are 165 possible broker-share pairs (11 brokers x 15 shares). However, there are only 119 pairs in which analysts associated with the broker actually issued at least one recommendation concerning a particular stock.

[12] To be precise, for the 10-day window we obtain the following numbers. For rank bid and ask it is 29.4% and 26.1%, for buy and sell it is 30.3% and 33.1%, and for bid and ask difference it is 44.5% and 40.3%, respectively. For the 5-day window we obtain the following ratios. For rank bid and ask it is 29% and 31%, for buy and sell it is 31% and 40%, and for bid and ask difference it reaches 45% and 43% , respectively.

after the recommendation is released. We should see a smaller distance from the best ask offer (frontier), i.e. the coefficient on the dummy variable "After" is expected to be negative when *Ask Difference* is used as a measure of trading activity. Similarly, *Ask Rank* should be smaller (negative coefficient); the coefficients when using (mandatory) *Sell* should also be negative.

- ***Bid difference*, *Bid rank*, and *Buy*.** Similarly, the bid behavior of the broker should reflect an opposite reaction to positive or negative recommendations compared to the ask case discussed above. If the broker sends a "true" positive signal, he should not buy the particular stock more actively, or at least should be more positive on the offer side compared to the no recommendation period and to the behavior of other brokers on the market.

Based on the expected reaction to the investment recommendation, for each trading variable[13] we can classify cases in which the broker systematically trades a) in line with the recommendation (or no reaction); or b) against the recommendation.

- *Buy* (*Bid difference*, *Bid rank*) variable used as a proxy
    a. Consistent: Consistent or no reaction behavior is formed by the following combinations of before/after coefficients.
        - negative before, insignificant or positive after
        - insignificant before, positive after
        - positive before, positive after
        - insignificant before, insignificant after.

    b. Inconsistent: Trading patterns that do not resonate with the released recommendation are characterized by the following combinations.
        - positive before, insignificant or negative after
        - insignificant before, negative after
        - negative before, negative after.
- *Sell* (*Ask difference*, *Ask rank*) variable used as a proxy
    a. Consistent combinations

[13] One could argue that results for the number of buys and sells should reflect a much stronger broker reaction regarding his own and others' recommendations. However, we expect to get similar answers, regardless of the trading proxy used.

- positive before, insignificant or negative after
- insignificant before, negative after
- negative before, negative after
- insignificant before, insignificant after.

b. Inconsistent combinations

- negative before, insignificant or positive after
- insignificant before, positive after
- positive before, positive after.

Table 2.3 (in the appendix) summarizes the consistent and inconsistent trading behavior of all brokers using a detailed combination of the possible outcomes presented in Table 2.2.

From Table 2.3 it seems clear that the inconsistency between investment recommendations and brokers' trading patterns is not just a coincidence. Very similar results are obtained for both time windows. As the inconsistent combinations indicate a recurring misuse of informational advantage stemming from affiliated analyst recommendations, Table 2.3 demonstrates how the broker's behavior systematically contradicts his recommendations across various stock groups and trading proxies. The percentages in Table 2.3 are computed from the aggregated numbers of all brokers. Therefore, they aggregate all brokers – those who do not use informational advantage and those that do. Clearly, the share of those cases in which we see *systematic* trading patterns that are inconsistent with the just-released recommendation is well above a Type I error; it is not random. Moreover, a very similar pattern occurs across all the variables used and the various type of stocks traded. However, local large companies exhibit slightly larger percentages compared to cross-listed companies. This may result from the fact that information leaks are easier when the company is listed on two or more markets and the investment recommendation is available to a larger number of subjects. Such leaks may provide the other local brokers with an opportunity to react to possible informational advantage, just as the affiliated brokers respond to their own recommendation.

The overall trading pattern shows that trading activity and the release of investment recommendations are not orthogonal; moreover, the observed figures support the statement that investment recommendations and their timing are either used to balance the broker’s inventories, or prior information about the released advice is used to make a short-term profit for proprietary trading. It is possible to conclude, therefore, that this segment of brokerage activity in the Czech Republic calls for additional regulation.

2.6 CONCLUSION

In this study we propose an innovative approach to testing the potential conflict of interest between analysts and traders, specifically the potential misuse of investment recommendations. In contrast to mainstream research associated with investment recommendations, we do not analyze the behavior of analysts, nor do we estimate their forecast error or test if they behave strategically. Instead, we take their investment recommendations as given, including the timing, and analyze the behavior of associated brokers around the time of the release of a recommendation.

The difference in our approach also lies in the use of different data sources. Rather than employing data from regulatory authorities, as other studies do, we rely on high-frequency data from internet-based trading platforms that allow us to identify the intra-day behavior of large brokers (market makers). We define time-weighted variables that profile a broker’s daily trading pattern, including his position on the bid and ask sides. The comprehensive information contained in trading proxies is used to analyze whether a broker’s behavior differs before and after a particular investment recommendation is released. Basically, if we observe systematic patterns across a long period of time, then we observe the manipulation or misuse of investment advice. We control for the effects of other investment recommendations and estimate the specification via a seemingly unrelated regression (SUR) framework for efficiency gains.

Although we may lack some information that is available only in confidential regulatory datasets, our results suggest that collapsed high-frequency trading data contains sufficient information to detect the suspicious behavior of a particular broker. Since our trading data is generated from a trading platform that is used primarily by retail and small investors, we cannot fully analyze the broker's interactions with large and institutional investors, which are usually done off the market. Our study is, however, better at capturing the misuse of the investment advice of large brokers over retail investors (or the informational advantage associated with such advice), which is a primary concern of regulators.

Our approach is demonstrated on trading data from the Prague Stock Exchange. Results confirm that on this market the above-mentioned conflict of interest exists and is quite severe. Assuming that this result can be generalized to all emerging stock markets, our findings support a need for the regulation of investment recommendations.

2.7 BIBLIOGRAPHY

Agrawal, A. and Chen, M. (2008). Do analyst conflicts matter? Evidence from stock recommendations. *Journal of Law and Economics,* Vol. 51 No. 3, pp. 503-537.

Asquith, P., Mibail, M. B., and Au, A. S. (2005). Information content of equity analyst reports. *Journal of Financial Economics,* Vol. 75 No. 2, pp. 245-282.

Barber, B., Lehavy, R., and Trueman, B. (2007). Comparing the stock recommendation performance of investment banks and independent research firms. *Journal of Financial Economics,* Vol. 85 No. 2, pp. 490-517.

Bhattacharya, U., Hackethal, A., Kaesler, S., Loos, B., and Meyer, S. (2012). Is unbiased financial advice to retail investors sufficient? Answers from a large field study. *Review of Financial Studies,* Advanced Access, first published online January 12, 2012 doi:10.1093/rfs/hhr127.

Chan, K. and Hameed, A. (2006). Stock price synchronicity and analyst coverage in emerging markets. *Journal of Financial Economics,* Vol. 80 No. 1, pp. 115-147.

Ertimur,Y., Sunder, J., and Sunder, V. S. (2007). Measure for measure: The relation between forecast accuracy and recommendation profitability of analysts. *Journal of Accounting Research,* Vol. 45 No. 3, pp. 567-606.

Fisch, J. E. (2006). Regulatory responses to investor irrationality: The case of the research analyst. *Lewis & Clark Law Review,* Vol. 10, pp. 57.

Girard, E. and Biswas, R. (2007). Trading volume and market volatility: Developed vs. emerging stock markets. *The Financial Review,* Vol. 42 No. 3, pp. 429-452.

Hanousek, J. and Filer, R. K. (2002). Data watch: Research data from transition economies. *Journal of Economic Perspectives,* Vol. 16 No. 3, pp. 225-240.

Hanousek, J. and Kopřiva, F. (2011). Detecting information-driven trading in a dealers' market. *Czech Journal of Economics and Finance,* Vol. 61 No. 1, pp. 204-229.

Irvine, P., Lipson, M., and Puckett, A. (2007). Tipping. *Review of Financial Studies,* Vol. 20 No. 3, pp. 741-768.

Kadan, O., Madureira, L., Wang, R., and Zach, T. (2009). Conflicts of interest and stock recommendations: The effects of the global settlement and related regulations. *Review of Financial Studies,* Vol. 22 No. 10, pp. 4189-4217.

Kiymaz, H. (2002). The stock market rumours and stock prices: A test of price pressure and size effect in an emerging market. *Applied Financial Economics,* Vol. 12 No. 7, pp. 469-474.

Li, X. (2005). The persistence of relative performance in stock recommendations of sell-side financial analysts. *Journal of Accounting & Economics,* Vol. 40 No. 1-3, pp. 129-152.

Lin, H.-W. and McNichols, M. F. (1998). Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics,* Vol. 25 No. 1, pp. 101-127.

Loh, R. K. and Stulz, R. M. (2011). When are analyst recommendation changes influential? *Review of Financial Studies,* Vol. 24 No. 2, pp. 593-627.

Michaely, R. and Womack, K. L. (1999). Conflict of interest and the credibility of underwriter analyst recommendations. *Review of Financial Studies,* Vol. 12 No. 4, pp. 653-686.

Morgan, J. and Stocken, P.C. (2003). An analysis of stock recommendations. *RAND Journal of Economics*, Vol. 34 No. 1, pp. 183-203.

Moshirian, F., Ng, D.. and Wu, E. (2009). The value of stock analysts' recommendations: Evidence from emerging markets. *International Review of Financial Analysis,* Vol. 18 No. 1-2, pp. 74-83.

SEC. (2002). Sec, NY Attorney General, NASD, NASAA, NYSE and state regulators announce historic agreement to reform investment practices. Available at http://www.oag.state.ny.us/press-release/sec-ny-attorney-general-nasd-nasaa-nyse-and-state-regulators-announce-historic.

Torre, A., Gozzi, J. C., and Schmukler, S. L. (2007). Stock market development under globalization: Whither the gains from reforms? *Journal of Banking & Finance,* Vol. 31 No. 6, pp. 1731-1754.

Womack, K. L. (1996). Do brokerage analysts' recommendations have investment value? *Journal of Finance,* Vol. 51 No. 1, pp. 137-167.

2.8 APPENDIX

Table 2.1: Number of quotes, trading days and investment recommendations

Name	Number of			Trading volume per day ($ mil)	Recommendations by		
	Trading days	Active brokers	Quotes per day		Local brokers	Other analysts	Percentage of positive
O2	1233	7-10	560	17.20	85	63	61%
CRA	188	2-8	95	1.57	7	1	50%
CEZ	1233	8-10	1168	53.50	114	93	69%
UNI	1233	4-8	371	6.10	65	11	37%
PM	1233	4-8	241	2.67	52	5	35%
EB	1234	6-9	687	12.20	78	149	66%
ZEN	1141	7-9	464	13.50	100	57	56%
ORCO	986	6-8	329	3.78	46	21	76%
CME	884	5-6	282	4.27	62	60	66%
ECM	517	3-7	245	2.33	15	3	72%
PN	510	3-8	251	2.23	26	2	79%
AAA	318	2-7	118	0.18	17	3	15%
VIG	229	4-5	148	0.44	6	22	75%
NWR	166	6-7	819	14.60	13	18	74%
KB	1232	6-10	786	21.10	70	53	49%
Total					756	561	

Notes: Recommendations include all types of recommendations: sell, hold, and buy.
Source: www.akcie.cz, www.ipoint.cz and authors' own computations.

Table 2.2: Summary of results for all brokers and all blue chip stocks

Panel A. Positive recommendation, time window 5 days before and after release

Before	After	Buy	Sell	Bid difference	Ask difference	Bid rank	Ask rank
Negative	Negative	3	2	13	8	6	4
	Insignificant	3	7	10	9	13	9
	Positive	2	1	3	2	0	0
Insignificant	Negative	11	5	10	7	7	7
	Insignificant	68	66	65	68	75	78
	Positive	9	13	5	5	5	3
Positive	Negative	3	2	1	1	2	4
	Insignificant	16	12	4	11	7	6
	Positive	4	10	8	8	4	8

Panel B. Positive recommendation, time window 10 days before and after release

Before	After	Buy	Sell	Bid difference	Ask difference	Bid rank	Ask rank
Negative	Negative	6	3	22	20	9	6
	Insignificant	4	9	10	7	11	10
	Positive	1	5	4	3	2	2
Insignificant	Negative	8	4	11	10	10	6
	Insignificant	63	59	50	52	70	72
	Positive	11	8	4	6	5	4
Positive	Negative	3	7	3	2	3	3
	Insignificant	16	11	6	12	3	6
	Positive	7	12	9	7	6	10

Note: The table contains all the possible combinations of outcomes for brokers' reactions to their own recommendations. Note that each case here represents a coefficient in specification (6), not a particular release of a recommendation. The reading of the table is illustrated thus: For example, in Panel B, number 6 in the upper left cell means that when the variable *Buy* (the number of shares bought as mandatory) was used as a proxy for trading behavior, overall we see 6 cases (brokers and stocks) when both coefficients before and after the release of recommendations were negative. Similarly, the combination positive before, positive after (the variable *Ask difference*) in the left column at the bottom of the table means that in 7 cases (stocks and brokers) we see a systematic positive response before and positive response after the recommendation was released. Again, we define the neighborhood of the recommendation as 10 trading days before and 10 trading days after, using the full model specification (6). Results for the other time (including asymmetric) windows are not presented here, but are available upon request. Source: authors' own computations.

Table 2.3: Broker's behavior systematically against his recommendation – sensitivity analysis, across various share groups and trading indicators (positive recommendations, 5- and 10-day windows)

	Time window	Buy and sell	Bid and ask difference	Bid and ask rank
All 15 companies	5 days	27%	22%	48%
	10 days	28%	27%	21%
Local large companies	5 days	34%	26%	19%
	10 days	30%	32%	29%
Cross-listed companies	5 days	23%	21%	13%
	10 days	33%	27%	15%

Note: The table contains a simple counting of each broker and stock of trading patterns, which are in line with or against the broker's own recommendation. The summary is based on the significance of the coefficients in specification (6). Below each behavioral proxy we present a ratio of all cases (broker and stock) in which we see the broker's behavior *systematically* contradicting his recommendations. The group of local large companies consists of O2, CEZ, UNI, PM, Zentiva, and KB. Cross-listed companies are represented by CME, EB, ORCO and NWR.
Source: Computed from Table 2, following the steps described in the paper.

Chapter 3

Constant Bet Size? Don't Bet on It! Testing Expected Utility Theory on Betfair Data

František Kopřiva*

CERGE-EI †

Abstract

I analyze the risk preferences of bettors using data from the world's largest betting exchange, Betfair. The assumption of a constant bet size, commonly used in the current literature, leads to an unrealistic model of bettors' decision making as a choice between a high return - low variance and low return - high variance bet, automatically implying risk-loving preferences of bettors. However, the data show that bettors bet different amounts on different odds. Thus, simply by introducing the computed average bet size at given odds I transform the bettor's decision problem into a standard choice between low return - low variance and high return - high variance bets, and I am able to correctly estimate the risk attitudes of bettors. Results indicate that bettors on Betfair are either risk neutral (tennis and soccer markets) or slightly risk loving (horse racing market). I further use the information on the average bet size to test the validity of EUT. The results suggest that, when facing a number of outcomes with different winning probabilities, bettors tend to overweight small and underweight large differences in probabilities, which is in direct contradiction to the linear probability weighting function implied by EUT.

JEL Classification: D01, D03, D81.
Keywords: decision making under risk, expected utility theory, betting exchanges

* Email addresses: frantisek.kopriva@cerge-ei.cz.
Address: CERGE-EI, P.O. Box 882, Politických vězňů 7, Prague 1, 111 21, Czech Republic.
The author would like to thank Levent Çelik, Randall Filer, Jan Hanousek, Eva Hromádková, Peter Katuščák, Fabio Michelucci, Andreas Ortmann, Avner Shaked, participants of CERGE-EI Brownbag seminar and participants of IAREP/SABE 2009 Halifax conference for helpful comments. Financial support of the Grant Agency of Charles University, Grant No. 34509 and research center grant No. LC542 of the Ministry of Education of the Czech Republic undertaken at CERGE-EI is gratefully acknowledged. The views expressed are those of the author and do not necessarily reflect the position of any of the affiliated institutions. An earlier version of this paper was awarded as Elsevier/IAREP/SABE Best Student Paper at the IAREP/SABE conference in Halifax 2009 and obtained 1st Prize in the Czech Economic Society competition Young Economist 2009.
All errors remaining in this text are the responsibility of the author(s).
† A joint workplace of the Center for Economic Research and Graduate Education, Charles University, and the Economics Institute of the Academy of Sciences of the Czech Republic.

3.1 INTRODUCTION

Expected utility theory (EUT) is considered to be one of the keystones of modern economic theory, yet its validity has been challenged by a large number of studies. The most prominent critique of EUT concerns the assumption that probability enters into people's preferences over lotteries linearly. As pointed out by Tversky and Kahneman (1992), the impact of the probability on the preferences over lotteries also depends on its distance from the so-called reference points – certainty and impossibility. This notion became the building block of *behavioral theories*[1] of decision making under risk and uncertainty, and led to the introduction of non-linear probability weighting functions.

A number of experiments document that behavioral theories are able to explain decision making under risk and uncertainty remarkably better than can EUT. There are, however, few empirical studies which assess the validity either of EUT or of behavioral theories in real situations. An innovative strand of empirical literature on this topic analyzes price data (odds) from *betting markets*.[2] These papers generally try to explain the existence of *favorite–long shot bias*[3], where bets on low probability outcome of events have a lower expected return than bets on high probability outcomes; an observation which is not consistent with standard EUT under the classic risk-averse utility function assumption. To explain this inconsistency, two lines of argument have been used – either positing a risk-loving utility function under EUT, or introducing probability weighting functions in behavioral theories (Snowberg and Wolfers, 2010).

The main drawback of previous studies on betting markets is, however, the absence of data on *bet size*. With the exception of Bradley (2003), they all posit an implicit assumption that bettors place the same amount of money on outcomes with different odds (i.e. that the bet size is constant irrespective of the probability of the outcome). As discussed in the next section, if we allow bettors to bet different amounts on outcomes with different odds, their decision problem is transformed into a standard choice between low return – low variance and high return – high variance bets. Thus,

[1] See for example Tversky and Kahneman (1992) - Cumulative prospect theory (CPT); and Quiggin (1982) - Rank-dependent expected utility theory (RDEU).
[2] Weitzman (1965), Ali (1977), Kanto et al. (1992), Hamid et al. (1996), Golec and Tamarkin (1998), Jullien and Salanie (2000), Bradley (2003), Gandhi (2007), Snowberg and Wolfers (2010).
[3] Favorite-long shot bias is one of the most prominent empirical regularities observed on betting data and was first noted by Griffith (1949) in horse racing betting markets.

the existence of long shot bias can be consistent with the standard risk-averse utility function under EUT, and need not resort to behavioral theories for explanation.

I design a novel empirical test to assess the validity of EUT vs. behavioral theories using information on how much bettors bet on different outcomes of a particular event. Further, applying data from the world's largest betting exchange, Betfair, to a wide range of events (tennis, soccer and horse races) for which outcomes span the whole range of winning probabilities allows me to analyze decision under risk and uncertainty under various scenarios. I draw conditioned subsamples based on the occurrence of a favorite in the event (i.e. event with/without a clear favorite),[4] using odds as a proxy for the objective probabilities of winning. These subsamples, and particularly the ratio of bets on different outcomes among events, provide rich information to test whether bettors weight probabilities linearly. As the conditioned subsamples fundamentally differ in their probability ranges of outcomes, finding substantial differences in how bettors assess the probabilities and determine the ratio of bet sizes on different outcomes in these conditioned subsamples strictly contradicts the linear probability weighting function assumption in EUT.

The paper is structured as follows. Section 3.2 analyzes the implications of the constant bet size assumption; section 3.3 outlines the methodology and estimation strategy. The data description is provided in section 3.4, section 3.5 presents and discusses the results and section 3.6 concludes.

3.2 CONSTANT BET SIZE ASSUMPTION

In recent years, the emergence of literature that analyzes the behavior of bettors on betting markets has fostered great progress in the understanding of decision making under risk and uncertainty. Early studies analyzing the risk preferences of bettors treat all events (races) as identical, group them by different characteristics, e.g. by odds intervals or position of horse in the race (see for example Ali, 1977 and Kanto et al., 1992), and conduct their analysis on the aggregated values. A further advance in the field was introduced by Jullien and Salanie (2000) who design a new methodology

[4] Conditioning on races with high-probability winning horses was used first by Golec and Tamarkin (1998) to address the problem of racetrack betting data, which consist of relatively few favorites (high-probability results) compared to the number of underdogs.

which does not require aggregation because, as they argue, betting behavior may differ with different characteristics of the particular horse race event. Given the limited availability of data, however, these papers all rely on the assumption of a representative bettor and constant bet size, i.e. they estimate the preferences of an average or *marginal bettor* who is indifferent among betting the same amount on different outcomes of a particular event. Ghandi (2007) relaxed this assumption by assuming a pool of heterogeneous agents that differ in their preferences over the horses. Effectively, however, he estimates the behavior of several marginal bettors who are indifferent between betting on two outcomes instead of betting on all outcomes.

The underlying assumption of the previous studies implies that, under EUT, a marginal bettor facing an event with two outcomes is indifferent between betting on the favorite or on the underdog. Assume a horse race with just two horses, one favorite with probability of winning p_F and decimal odds[5] O_F , and one underdog with probability p_U ($p_U = 1 - p_F$) and odds O_U, where $p_U < p_F$ and $O_U > O_F$. The marginal bettor bets constant amount B (i.e., bet size is constant). Then, the marginal bettor is indifferent between betting on the favorite vs. betting on the underdog if and only if

$$EU_F = p_F u(M + (O_F - 1)B) + (1 - p_F)u(M - B) \tag{3.1}$$
$$= u(M + (O_U - 1)B) + (1 - p_U)u(M - B) = EU_U$$
$$p_F u\big(M + \big(O_f - 1\big)B\big) - p_U u(M + (O_U - 1)B) = (p_F - p_U)u(M - B)$$

In the presence of long shot bias the return on favorite is higher than return on underdog:

$$p_F(M + (O_F - 1)B) + (1 - p_F)(M - B) \tag{3.2}$$
$$> p_U(M + (O_U - 1)B) + (1 - p_U)(M - B)$$
$$p_F(M + (O_F - 1)B) - p_U(M + (O_U - 1)B) > (p_F - p_U)(M - B)$$

[5] Bookmakers in Europe, the UK and the US have different standards of displaying odds. Further in the text I use the European style of odds, also called decimal odds. Odds $O^E = 1.40$ imply that the bet will bring payoff $(O^E - 1)B = 0.40B$ if the outcome wins and $-B$ if the outcome loses. In the UK odds are usually displayed in the form $O^{UK} = x/y = 2/5 \; s.t. O^E = (x + y)/y$. In the US odds are displayed in the form +X or –X where the negative odds are for those bets where the payoff is lower than the bet. In our case the US odds are $O^{US} = -X = -250$; $O^E = 1 + 100/X$ if the US odds are negative and $O^E = 1 + X/100$ if the US odds are positive.

Without loss of generality we can assume that $M - B = 0$ and $u(0) = 0$. Thus,

$$\frac{u(M + (O_U - 1)B)}{u(M + (O_F - 1)B)} = \frac{p_F}{p_U} > \frac{M + (O_U - 1)B}{M + (O_F - 1)B} \quad (3.3)$$

As $M + (O_U - 1)B > M + (O_F - 1)B$, the utility function has to be convex at least in some range of the interval $(M + (O_F - 1)B, M + (O_U - 1)B)$ – i.e., the marginal bettor has to exhibit risk-loving preferences.

Following the same line of thought, Snowberg and Wolfers (2010) point out that, in the presence of long shot bias and without assuming non-linear probability weighting function, one has to allow for the risk-loving preferences of a marginal bettor under EUT. They recognize that using information on price data (odds) alone for simple bets (e.g., bet on the winner of a horse race) is not sufficient to confirm the validity of EUT vs. behavioral theories. Instead, they compare the price data on simple bets – win bets and compound bets – exactas, trifectas and quinellas (exotic bets on the order of the first two or three horses and on the two horses to come first in the race in either order) and find evidence in favor of behavioral theories. Therefore, they conclude that the long shot bias is mainly driven by the misperception of probabilities rather than by the risk-loving preferences of rational bettors.

Nevertheless, these previous studies lack important information, namely how much people bet on different outcomes with different winning probabilities. The only study to account for bet size in the analysis of bettors' behavior is Bradley (2003). As he does not have data on bet size, he performs his analysis using the imputed optimal bet size of a representative bettor. By assuming that the only utility that a bettor has from a bet is derived from expected return and variance, he computes the optimal bet as an argument for the maximum weighted expected utility given the probabilities and odds. However, he still does not consider the main reason for including bet size, namely how it changes the estimates of the revealed risk preferences of the marginal bettor. If one allows the marginal bettor to bet amount B_F on the favorite and B_U on the underdog, the above stated key formula for identification of his risk preferences changes to

$$\begin{aligned} EU_F &= p_F u(M + (O_F - 1)B_F) + (1 - p_F)u(M - B_F) \\ &= p_U u(M + (O_U - 1)B_U) + (1 - p_U)u(M - B_U) = EU_U \end{aligned} \quad (3.4)$$

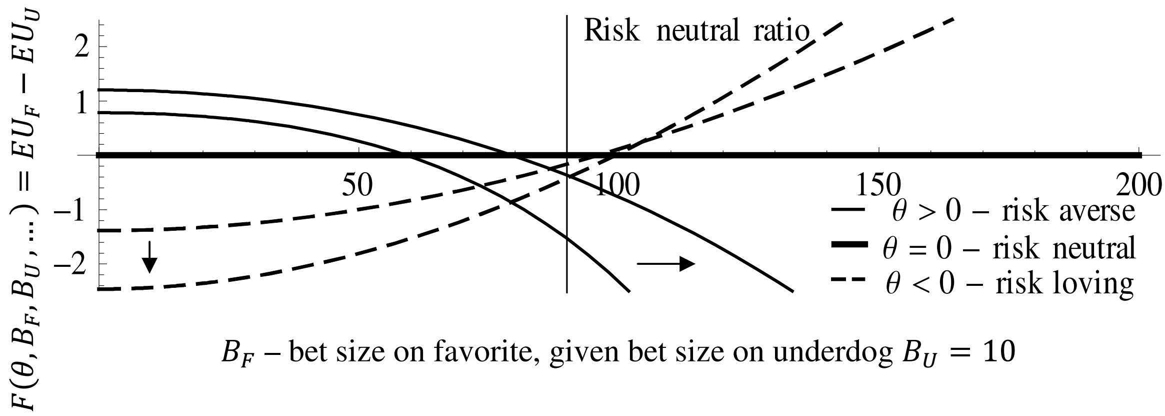
Let me define for the further analysis the following function

$$F(\theta, B_F, B_U, p_F, p_U, O_F, O_U, M) = EU_F - EU_U \qquad (3.5)$$

where θ represents the risk preference parameter of the utility function. Contrary to the previous case, conditional on the ratio of the average bet sizes on the two outcomes, equation (3.4) may have none, one, or two solutions under standard utility assumptions. Henceforward, all examples are done under EUT with the standard CARA utility function assumption $u(x, \theta) = \left(1 - e^{-\theta x}\right)/\theta$, where $\theta > 0$ corresponds to risk-averse preferences.[6]

In the first step, I focus on the analysis of the *fair odds* case (i.e., no long shot bias present). Under EUT the risk-neutral bettor should be willing to bet any amount of money, which is unrealistic. Therefore, it is more reasonable to define a risk-neutral bettor in terms of the bet size ratio as the limit case between a risk-loving and risk-averse bettor (see Figure 3.1 below).

Figure 3.1: Bet size ratio with fair odds



Note: The figure depicts the difference of expected utility of betting on the favorite and betting on the underdog under fair odds with the bet size on the favorite on the horizontal axis, for different risk aversity parameters θ of the CARA utility function. The difference is illustrated on an example, where the probability of the favorite winning is 90% and the probability of the underdog winning is 10%. The arrows illustrate the shift towards less risk-averse values of parameter θ.

Mathematically, the risk-neutral bettor would choose, under fair odds, the ratio:

$$B_F/B_U = \lim_{\theta \to 0}(B_F/B_U \textit{ such that } F(\theta, B_F, B_U, \ldots) = 0), \text{ with solution}$$

$$B_F/B_U = \frac{p_F}{\sqrt{p_F(1-p_F)}} \Big/ \frac{p_U}{\sqrt{p_U(1-p_U)}}$$

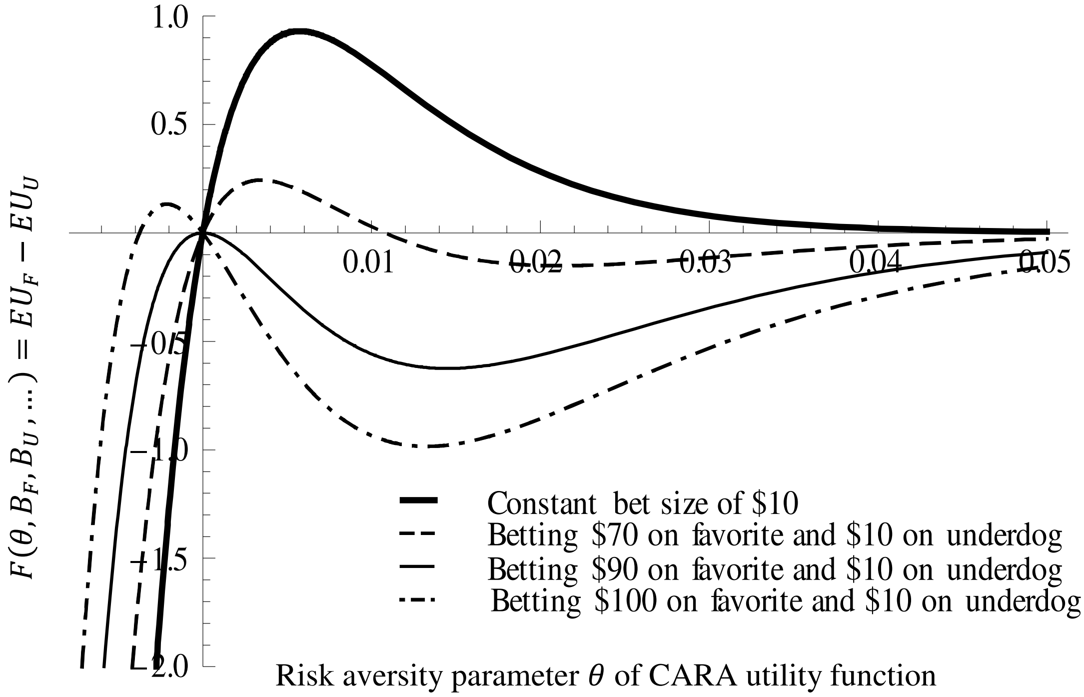
[6] One would get similar results with the standard CRRA utility function $u(x, \rho) = x^{1-\rho}/(1-\rho)$

In the case with two outcomes, the previous expression boils down to

$$B_F/B_U = p_F/p_U \; as \; p_F + p_U = 1$$

In the example depicted in Figure 3.1, this corresponds to the $B_F = 90$ (bet ratio 9:1). This analysis can be used to derive the risk preferences of the bettor from the ratio of bets that I would observe in the data without long shot bias. In Figure 3.2, I distinguish two possible cases of bet ratios B_F/B_U: 1.) $B_F/B_U \leq 1$: This case corresponds to the constant bet size assumption (thick line in Figure 3.2). In this case, the equation (REF) has one closed solution in $\theta = 0$ and one limit solution for $\theta \to \infty$. However, the above analysis implies that the ratio of those bets consistent with the behavior of a risk-neutral bettor is definitely higher than 1. Thus, I pick the limit solution $\theta \to \infty$ as the correct one and interpret the risk preferences of the marginal bettor who bets constant amounts on both outcomes as extremely risk averse.[7]

Figure 3.2: Eliciting risk preferences from bet size ratio under fair odds



Note: The figure depicts the difference of expected utility of betting on the favorite and betting on the underdog under fair odds with the risk aversity parameter θ of the CARA utility function on the horizontal axis, given the bet size on the favorite and on the underdog. The difference is illustrated on an example, where the probability of the favorite winning is 90%, and the probability of the underdog winning is 10%.

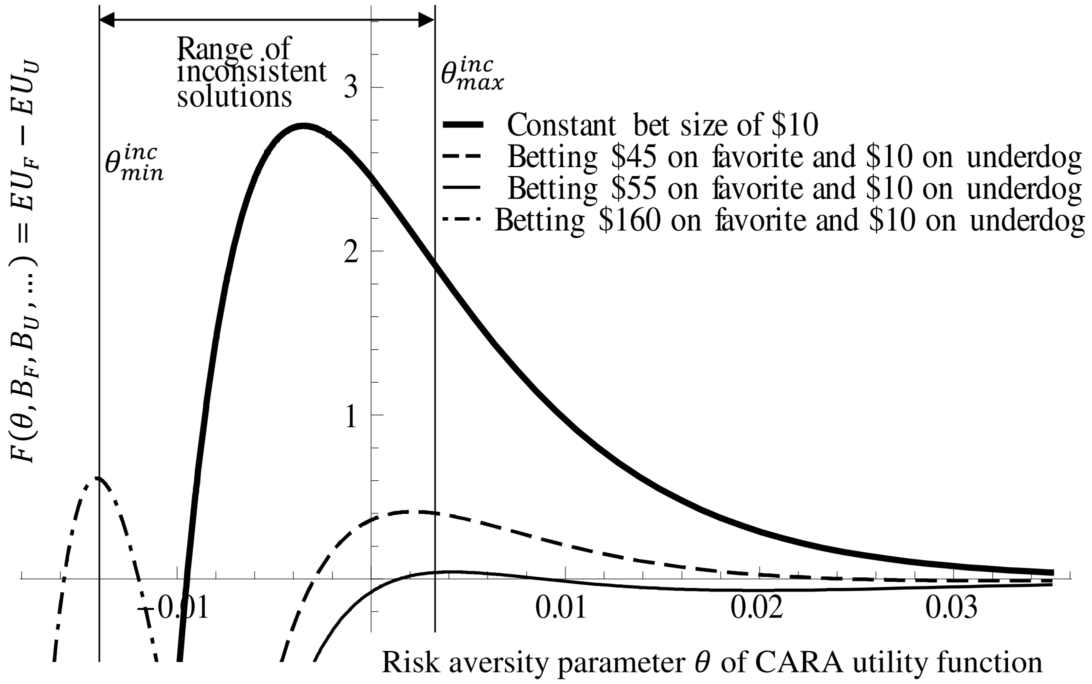
---

[7] This behavior may also be interpreted as a decision to bet a certain amount of money but an unwillingness to bet/lose any more money than that. Such behavior will be more consistent with immense risk-averse preferences than with risk neutral preferences.

2.) $B_F/B_U > 1$: In line with the previous argument, the risk preferences continuously shift from extremely risk averse to extremely risk loving. Based on the bet size ratio we can distinguish two cases: if the bet size ratio is lower than the ratio chosen by the risk-neutral bettor, then the marginal bettor is risk averse (Figure 3.2, dashed line); whereas if the bet size ratio is higher, we can infer that the marginal bettor has risk-loving preferences (Figure 3.2, dot-and-dashed line), with a risk-neutral ratio of bets between them (Figure 3.2, thin line).

In the second step, the analysis is generalized for the presence of long shot bias. Similar to the case with fair odds, the main assumption is that the ratio B_F/B_U, consistent with the indifference of the marginal bettor, is increasing with decreasing risk aversion. Thus, if I find a solution that does not satisfy this assumption I consider it to be inconsistent.

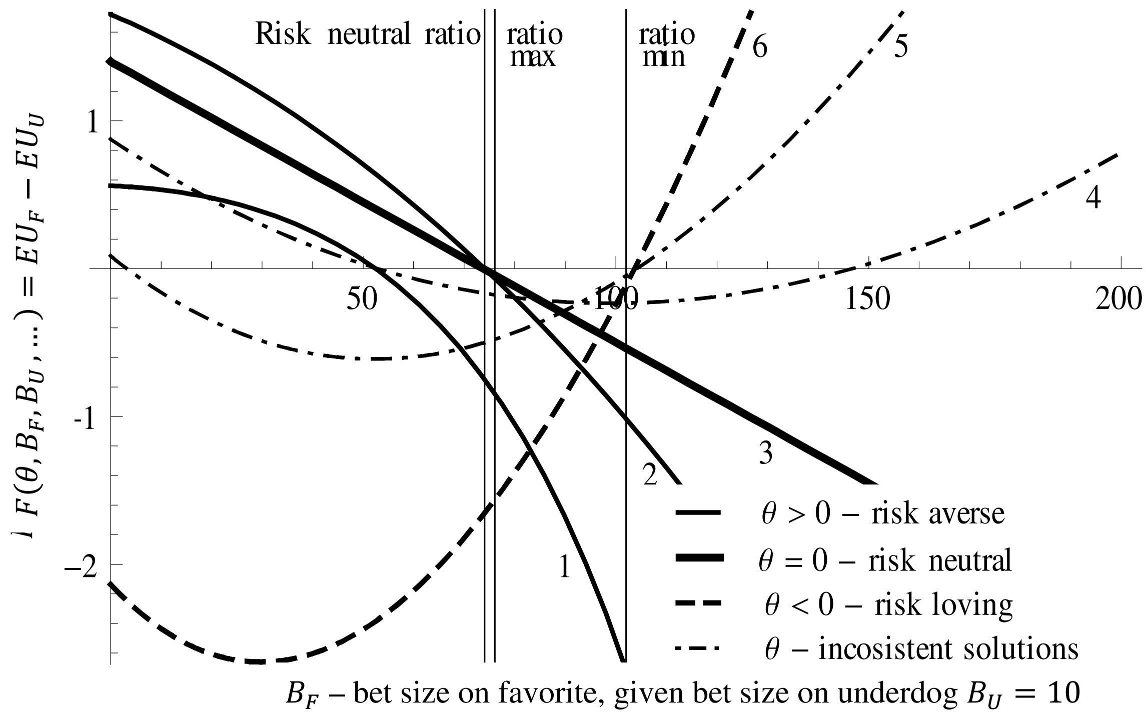
Figure 3.3: Eliciting risk preferences from bet size ratio under long shot bias



Note: The figure depicts the difference of expected utility of betting on the favorite and betting on the underdog under long shot bias with the risk aversity parameter θ of the CARA utility function on the horizontal axis, given the bet size on the favorite and on the underdog. Long shot bias is present, i.e., odds on the favorite are 1.05 (with the probability of the favorite winning 90%), and odds on the underdog are 7 (probability of winning 10%), leading to an expected return of -0.06% on the favorite and -0.3% on the underdog.

As presented in Figure 3.3, there exists a range $(\theta_{min}^{inc}, \theta_{max}^{inc})$ of risk parameter theta, which corresponds to inconsistent solutions (roots) of equation (3.4).[8] In this range, the lower risk aversion is connected to lower bet size ratio, contradicting the basic assumption. To better illustrate the inconsistency, Figure 3.4 depicts 6 lines corresponding with decreasing θ from strongly risk-averse (line 1) to strongly risk-loving (line 6) preferences. Moving away from strongly risk-averse preferences, the bet size ratio increases until it reaches its maximum (line 2), marked as ratio max in the figure for $\theta = \theta_{max}^{inc}$ (from the previous Figure 3.3).

Figure 3.4: Bet size ratio under long shot bias



Note: The figure depicts the difference of expected utility of betting on the favorite and betting on the underdog under long shot bias with the bet size on the favorite on the horizontal axis, given the risk aversity parameter θ of the CARA utility function. The difference is illustrated on an example, where the probability of the favorite winning is 90% and the probability of the underdog winning is 10%. Lines are numbered from most risk averse (1) to least risk averse/most risk loving (6).

Decreasing θ even further, the bet size ratio starts to decrease (lines 3, 4 and 5 in Figure 3.4). These lines correspond to inconsistent values of θ within the range $(\theta_{min}^{inc}, \theta_{max}^{inc})$. Finally, starting at θ_{min}^{inc} (representing risk-loving preferences), the bet size ratio starts increasing again ($\theta < \theta_{min}^{inc}$; line 6). At this point the bet size ratio has reached its

[8] One can show that if equation (3.4) has one inconsistent solution, it has a consistent solution (including the limit solution $\theta \to \infty$).

minimum for risk-loving preferences, marked as ratio min in Figure 3.4. For the ratio of bets between (ratio max; ratio min), no solution to equation (3.4) exists.

It should be stressed that the solution for constant bet size lies within the range of inconsistent solutions with $\theta < 0$ (Figure 3.3, thick dark line). This has led authors who held to the constant bet assumption to the erroneous conclusion that bettors have to exhibit risk-loving preferences under EUT.

3.3 METHODOLOGY

The microstructure of Betfair as a typical *betting exchange* differs from the classic betting markets, and in certain respects it is more like financial markets. Every market on the exchange (for example the event on the winner of a horse race) consists of several outcomes with ex-ante objective probabilities of happening $p_1, \dots, p_N$. For every outcome of the event bettors have two options: To place a bet that the outcome will happen – the *back bet* in Betfair terminology; or to place a bet that the outcome will not happen – the *lay bet*. The Betfair betting exchange is designed as an order-driven market where bettors can place either limit orders or market orders. *Market order* means that the bettor just chooses a side (buy or sell on classic markets, back or lay on Betfair), a particular outcome, and a bet size. The bet is then matched at the best possible price available on the market. *Limit order* means that the bettor is not satisfied with any market odds available at the moment and chooses not only the side, outcome, and volume, but also the odds at which he is willing to bet. The bet then waits on the market until it is matched by some other bettor. Therefore, when placing a limit order, the bettor has to decide whether to place a back or lay bet and has to stipulate the odds and bet size. On the other hand, when placing a market order, the bettor hits the odds already available on the market and chooses just the bet size and side of the market.

Assume that the bettor decides to place a back bet (the outcome will happen) on outcome 1 of volume one dollar at odds O_1. With probability $p_{1,}$ outcome 1 occurs and the bet yields profit$(1-\tau)R_1 = (1-\tau)(O_1 - 1)$, where τ is the commission (2–5%) that Betfair charges on the net winnings. If outcome 1 does not occur the bettor will lose one dollar. If the bettor places a lay bet (the outcome will not happen) on outcome 1 of volume one dollar at odds O_1, the bet yields profit $(1-\tau)$ dollars if outcome 1 does not occur and loss $-R_1$ if outcome 1 occurs. As I focus on those markets with one possible winner, the probabilities $p_1, \dots, p_N$ sum up to one. Thus, backing an outcome at odds is actually the same as laying all the other outcomes at respective odds.

Generally, bettors may have different prior beliefs about the underlying probabilities of winning of the outcomes. However, they update their beliefs using market prices. Therefore, in equilibrium, all bettors can use the odds to infer the true underlying probabilities of the outcomes. Further, bettors can be divided into three main categories – common bettors, bookmakers, and traders. I assume that the majority of Betfair customers (more than 2 million people) may be characterized as *common bettors*, who typically bet only on one outcome and mostly place back market orders. I discuss this particular assumption and its implications on the results in the Appendix.

The other two types of bettors – bookmakers and traders – are professional bettors who use the Betfair markets for making a profit. I assume that bookmakers post mostly large volume limit orders and only occasionally use market orders to balance their portfolios.[9] I consider them to be risk neutral, as they basically try to balance their liabilities and earn a profit from the spread. The third type of bettor, traders, are similar to bookmakers. Their main concern, however, is not to make money from the spread but to identify arbitrage opportunities. Therefore, they place both limit and market orders, open and close their positions, and earn their profit from the differences of the asset price over time. These bettors are, therefore, usually placing large volume orders and the size of their bets is balanced with respect to the odds, i.e., they are also acting as risk-neutral bettors.

In September 2008 Betfair introduced a new policy of "premium charges", requiring customers who consistently win to pay at least 20% of their total profits in commission or other charges. Although this rule was aimed at bookmakers and traders, Betfair claimed that it affected less than 0.5% of its customers. Since, according to this statement, bookmakers and traders make up less than 0.5% of all bettors, I direct my attention to the majority – common bettors – when analyzing the risk attitude of the general population of bettors.

[9] In analyzing the in-trade soccer markets, Gil and Levitt (2007) point out that the endogenously emerged market makers were on one side of the trade for 65 percent when the markets were inplay, i.e. betting during the running event.

Due to the differences in market microstructure and in the behavior of bettors on different sports markets I analyze the tennis, soccer and horse race events separately. My empirical methodology follows the seminal paper of Jullien and Salanie (2000). For each event the common bettors face the following successive decisions:

1) The bettor decides whether or not to bet;
2) Conditional on the characteristics of the event, outcomes, and subjective probabilities of winning, the bettor decides how much he would be willing to bet on every outcome;
3) After observing the odds the bettor chooses which outcome in the event he will bet on.

The decisions in the first and second steps depend on both the event/outcome parameters and the personal characteristics of each bettor. All bettors have their own motives for betting and as no information about their personal characteristics is known, I do not model this decision. Further, I assume that the decisions of common bettors can be represented by the behavior of a representative agent – *marginal bettor* – with initial wealth M. The marginal bettor is able to anticipate from the equilibrium odds the true probability of winning of particular outcomes in the event. Furthermore, under EUT, for every two outcomes i, j on the market with given odds O_i and O_j, probabilities p_i and p_j, and average bet sizes B_i and B_j, the marginal bettor with given utility function and risk preference parameter θ is indifferent between betting on these two outcomes, such that

$$\begin{aligned} p_i u(M + B_i(1-\tau)R_i, \theta) + (1-p_i)u(M - B_i, \theta) \\ = p_j u\big(M + B_j(1-\tau)R_j, \theta\big) + \big(1-p_j\big)u\big(M - B_j, \theta\big). \end{aligned}$$

As the probabilities sum up to one, I obtain the analytical solution for probabilities in the form

$$p_i = \frac{\dfrac{1 + \sum_{j=1}^{N} \dfrac{u\big(M - B_j, \theta\big)}{u\big(M + B_j(1-\tau)R_j, \theta\big) - u\big(M - B_j, \theta\big)}}{\sum_{j=1}^{N} \dfrac{1}{u\big(M + B_j(1-\tau)R_j, \theta\big) - u\big(M - B_j, \theta\big)}} - u(M - B_i, \theta)}{u(M + B_i(1-\tau)R_i, \theta) - u(M - B_i, \theta)} \tag{3.6}$$

As I do not observe any information about the wealth or income of the marginal bettor, I use the CARA utility function in the form $u(x,\theta) = \left(1 - e^{-\theta x}\right)/\theta$; otherwise the parameter estimates would be based either on the arbitrary choice of wealth M, or would have to be estimated as an additional parameter. Each p_i is uniquely defined by the set of $B_i's$, $R_i's$, and θ. Therefore, similarly as in Julienne and Salanie (2000), θ is estimated by Maximum Likelihood Estimation using formula (3.6) of the probability of the winning outcome. The likelihood function is then a sum of logs of probabilities for ex-post winners p_W from each match:

$$L(\theta) = \sum_{c=1}^{C} \log p_W(R_1^c, \dots, R_N^c, B_1^c, \dots, B_N^c, \theta) \tag{3.7}$$

One of the key assumptions of alternative behavioral theories of decision making under uncertainty is that probabilities enter the formula of expected utility in a non-linear form. In other words, bettors have a non-linear probability weighting function. It is possible, however, to test the validity of EUT without explicitly formalizing the alternative theories. If the assumption of a linear weighting function of EUT is correct, then the estimated risk aversion parameters of the marginal bettor should be the same regardless of the winning probabilities of players/teams/horses. Therefore, for each sport I draw two subsamples: one with the presence of strong favorites (and large differences in winning probabilities between outcomes) and the other without a favorite (and small differences in winning probabilities between outcomes). Under the null hypothesis, EUT holds and therefore the estimates on the subsamples should not be statistically different from each other. If the results differ, EUT can be rejected in favor of theories with non-linear weighting functions of probabilities.

3.4 Data

I use aggregated historical data from the world's largest betting exchange, Betfair, for all tennis, soccer and horse race winners' markets between June 2004 and December 2008. All the studies described in Section 3.2 analyze the risk preferences of bettors only on horse race markets. However, horse race events usually consist of a large number of outcomes (horses) with a low probability of winning and only a few outcomes with a high probability of winning. This could lead to a situation in which I would estimate the risk preferences of bettors just on those bets with a low probability of winning. As pointed out by Forrest and McHale (2007), however, the tennis betting markets possess the nice feature of having a nearly complete distribution of events with outcomes over the whole probability range. Using data from the tennis and soccer markets, then, allows me to analyze the behavior of bettors facing the complete set of probabilities.

For each outcome on every market and for each odds at which at least one bet was placed, the data from Betfair include information on the number of bets placed, total volume matched, date and time of the first and last matched bet on given odds, scheduled and actual start of the event, indicator of inplay bets[10], and indicator of the winning outcome. Although on Betfair one can also place bets during the matches, I only use data on those bets that were placed before the start of the match or race, so as to analyze the ex-ante risk attitudes rather than the reaction of bettors to news from the ongoing match.

Recent studies on the risk attitude of bettors (e.g. Jullien and Salanie, 2000; Ghandi, 2007) have employed starting prices - the odds valid at the start of the event. At betting exchange markets there are, however, always two values of odds – back and lay. Moreover, the odds tend to fluctuate even before the start of the event; using just the final value of odds would result in loss of information about the volume matched and the number of bets placed at odds slightly different than the final odds.[11] I therefore use the weighted average of odds (by volume matched) at which at least one bet was placed during the last two hours preceding the start of the match for soccer and tennis, and during the last five minutes preceding the start of the race for horse racing. The aim

[10] Bets placed after the event has started.

[11] I effectively treat these small fluctuations as if the market was already in equilibrium.

was to determine a time interval reasonably long enough to encompass small fluctuations of odds around equilibrium, yet still short enough to screen out large changes of odds signaling that the market is not in equilibrium.[12] The different lengths of time intervals for soccer, tennis, and horse racing reflect the different microstructure of the markets in these sports. Due to the lower number of soccer and tennis markets, as well as the lower number of outcomes on these markets and longer time intervals between these events, the odds on soccer and tennis markets do not often exhibit large fluctuations before the start of the event.

The liquidity of Betfair markets varies tremendously, being as low as two bets with £4 volume matched to as high as 42,421 bets and £9,496,375 volume matched. Due to the lack of liquidity, I further restrict the analysis to those markets at which at least 20 bets have been placed on each outcome of the event. In the case of tennis and soccer matches the number of outcomes is given, yet for horse races the number of outcomes differs for each race. Thus, to assure that all the outcomes of horse race events are accounted for, I ruled out those events where the sum of imputed probabilities was lower than *0.98* and considered only those events where the total number of outcomes (horses) was lower or equal to 13.[13] All these steps restricted the analysis to 17,371 tennis match winner markets, 70,831 soccer match winner markets, and 59,386 horse race winner markets.

For further analysis of the risk preferences of marginal bettors, I use the *average bet size* computed as the volume matched over the number of bets from all odds at which at least one bet was made during the relevant time interval preceding the start of the event. The volume matched encompasses both the volume of market and limit matched orders on the back and lay side, and the number of bets is the sum of both back and lay bets. So, in fact, I use the average size of both back and lay bets. Average bet size varies remarkably with odds, suggesting that bettors bet different amounts on different odds, and justifying the importance of including the bet size in analysis. The average bet sizes for all three sports are presented in Figure 3.8 in the Appendix.

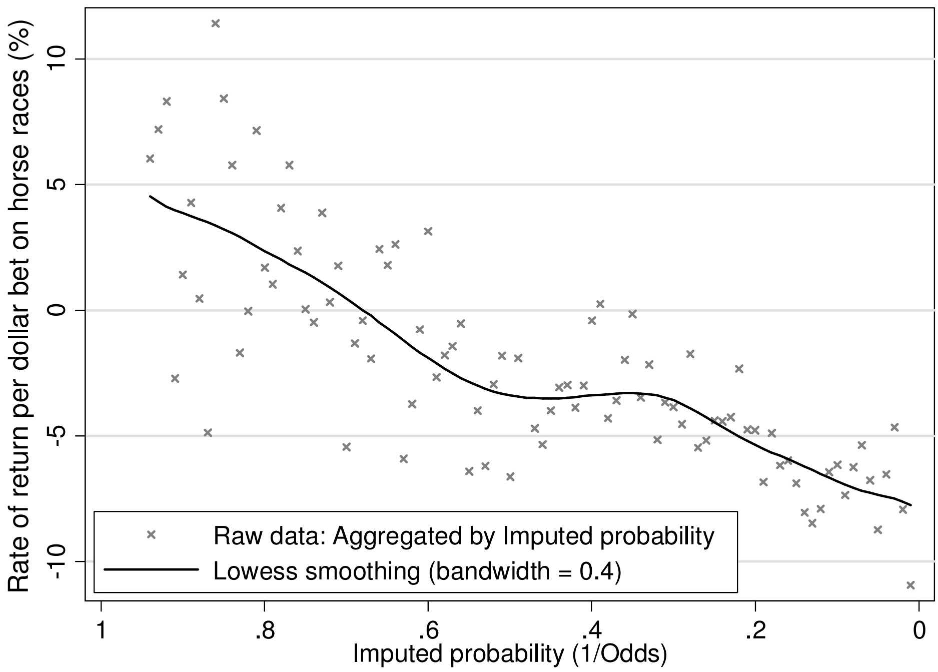
[12] I considered intervals in the range of 2 minutes - 10 hours before the start of the match. I chose the longest interval in which the average fluctuation of probability representation of odds (i.e. imputed probability equal to the inverse value of odds) was still lower than 3%.

[13] Races with more than 13 horses account for less than 8% of the total number of races.

With the available data I am not able to distinguish between the average back bet size and the average lay bet size as I do not have information on the number of back or lay orders. Thus, in further estimation I assume that the computed average bet size corresponds to the average back bet size. In the Appendix I provide a mathematical proof that under plausible assumptions on the behavior of bettors this approach delivers reliable and correctly interpreted estimation results.

As pointed out before, a usual characteristic of betting market data is so-called favorite-long shot bias. Smith et al. (2006) suggest that favorite-long shot bias should be lower on betting exchanges. My data are consonant with this, as they exhibit smaller long shot bias on horse race markets (see Figure 3.5). Still, Figures 3.6 and 3.7 in the Appendix show the presence of fairly strong long shot bias on the tennis and soccer match winner markets.

Figure 3.5: Expected return per dollar bet on horse races at Betfair



Note: number of observations used: 59,386 horse races.

3.5 RESULTS

In the first part, I focused on the importance of accounting for bet size in the analysis of risk preferences of bettors. As discussed above, when we use just price data, the estimates are driven solely by the long shot bias. In Table 3.1 the estimates of risk aversion for bettors, assuming constant bet size, are presented. The results indicate that the marginal bettor has risk-loving preferences, a finding similar to that of Jullien and Salanie (2000).

Table 3.1: Estimates of risk aversion parameter of CARA utility function, assuming constant bet size

Market	θB	*s.d.*	*p-value*	*95% CI_{lower}*	*95% CI_{upper}*
Tennis	-0.036	0.0109	0.001	-0.0576	-0.0150
Soccer	-0.015	0.0046	0.001	-0.0244	-0.0063
Horce races	-0.003	0.0006	0.000	-0.0042	0.0017

Note: number of observations used in the estimation: tennis – 17,371 obs., soccer – 70, 831 obs., horse races – 59,386 obs.

Further, the estimated coefficient θB consist of both the parameter of risk aversion θ and the average bet size B, which is £20 for horse racing, £45 for soccer, and £107 for tennis. This implies that the estimates of risk aversion parameter θ on different sports at Betfair are of comparable size, but all of them are significantly smaller than the estimates of Jullien and Salanie (2000). One reason may be the higher competition among bookmakers at Betfair markets, but also that as part of the data cleaning procedure I discarded all events with fewer than 20 bets on any of the outcomes and therefore screened out low liquidity markets, i.e. ones facing lower competition among bookmakers.

As explained in Section 3.2, bet size is key to the analysis of bettors' behavior, as bettors do not usually bet the same amount on different odds. Indeed, accounting for bet size dramatically changes the results for all sport types, as presented in Table 3.2. These differences between the markets on different sports raise questions about the appropriateness of EUT.

Table 3.2: Estimates of risk aversion parameter of CARA utility function, accounting for different bet size

Market	θ	*s.d.*	*p-value*	*95% CI_{lower}*	*95% CI_{upper}*
Tennis	-0.0003	0.0002	0.225	-0.0009	0.0002
Soccer	0.0001	0.0001	0.222	-0.0001	0.0003
Horce races	-0.0005	0.0001	0.000	-0.0006	-0.0004

Note: number of observations used in the estimation: tennis – 17, 371 obs., soccer – 70, 831 obs., horse races – 59, 386 obs.

In the second step I test the key difference between EUT and behavioral theories, namely the assumption that bettors have a linear probability weighting function. If the EUT model of bettors' behavior is correct, we should obtain the same estimates of risk preferences over the whole range of probabilities. Therefore, I draw two types of subsamples from the data on each sport. The first type is a subsample with favorites, where I condition the selection of events on the presence of a strong favorite. Due to the different number of outcomes in the particular sport[14], I include the event in the sample only if there exist: (a) a tennis player with odds lower than 1.25 in tennis (imputed probability of winning greater than 80%); (b) a team with odds lower than 2.0 in soccer (imputed probability of winning greater than 50%); and (c) a horse with odds lower than 3.0 in the horse race (imputed probability of winning greater than 33%). I use the odds as a proxy for the objective probabilities of winning. The second type of subsample consists of events without any favorite, i.e. I include the event in the sample only if both players have odds greater than 1.5 for tennis (imputed probability of winning lower than 66%); if all outcomes have odds greater than 2.3 in soccer (imputed probability of winning lower than 43%); and if all horses in the race have odds greater than 4.0 in the horse races (imputed probability of winning lower than 25%). Under EUT, the risk preferences of the representative bettor should not differ regardless of whether he is betting on an event with a strong favorite or on an event without large differences in the winning probabilities of outcomes. Therefore, by comparing the results of the two types of subsamples I can easily test whether a marginal bettor has a linear weighting function of probabilities.

[14] There are two players for tennis, three outcomes for soccer and usually more than six outcomes for horse races leading to significant differences in the objective probabilities of winning between the outcomes in these sports.

Table 3.3: Tennis markets - Estimates of risk aversion parameter of CARA utility function on subsamples defined by the presence of favorite, accounting for bet size

Market	θ	*s.d.*	*p-value*	*95% CI_{lower}*	*95% CI_{upper}*
All events	-0.0003	0.0002	0.225	-0.0009	0.0002
- with favorites	0.0004	0.0004	0.277	-0.0003	0.0011
- no favorites	-0.0013	0.0005	0.007	-0.0023	-0.0004

Note: number of observations used in the estimation: all events – 17,371 obs., with favorites – 4,101 obs., no favorites – 7,787 obs.

Table 3.4: Soccer markets - Estimates of risk aversion parameter of CARA utility function on subsamples defined by the presence of favorite, accounting for bet size

Market	θ	*s.d.*	*p-value*	*95% CI_{lower}*	*95% CI_{upper}*
All events	0.0001	0.0001	0.222	-0.0001	0.0003
- with favorites	0.0003	0.0001	0.011	0.0001	0.0005
- no favorites	-0.0004	0.0002	0.030	-0.0008	-0.0001

Note: number of observations used in the estimation: all events – 70,831 obs., with favorites – 31,287 obs., no favorites – 23,162 obs.

The results for tennis, soccer and horse races are presented in Tables 3.3–3.5. Estimates of the risk aversion parameter for the subsamples with a favorite and without a favorite are significantly different from each other for all three sports. I can therefore reject the null hypothesis of a linear probability weighting function in favor of its non-linear counterparts. Details of the estimation for particular sports are discussed below.

Results for tennis and soccer indicate that the ratio of the bets on outcomes with small differences in probabilities is higher than the ratio consistent with the behavior of risk-neutral bettors. This might suggest that people overweight small differences in probabilities. On the other hand, the opposite is true on markets with strong favorites, where the ratio of the amount placed on the more probable outcome to the amount placed on the less probable outcome is lower in comparison with risk-neutral bettors. This might suggest that people either underweight large differences in probabilities or simply underweight the large probabilities near the reference point 1. Another possible explanation is that bettors have restrictions on their maximum bet size; that is, when the model of risk-neutral bettors implies remarkably high bets for high probable outcomes, the maximum bet size may function as a binding constraint, resulting in a significantly lower bet ratio of bets on events with strong favorites than on events without any favorites. In both cases, however, I can reject the hypothesis that the marginal bettor at Betfair has a linear weighting function of probabilities.

These results bring further insight to the theories of Tversky and Kahneman (1992). They assume that people underweight large probabilities and overweight small probabilities, i.e., that zero and certainty serve as reference points from which people offset their perception of probabilities. My results suggest that even particular outcomes serve each other as reference points, which leads to observed overweighting of small differences in probabilities and underweighting of large differences in probabilities.

Table 3.5: Horse race markets - Estimates of risk aversion parameter of CARA utility function on subsamples defined by the presence of favorite, accounting for bet size

Market	θ	*Std.dev.*	*p-value*	*95% CI_{lower}*	*95% CI_{upper}*
All events	-0.0005	0.0001	0.000	-0.0006	0.0004
- with favorites	-0.0008	0.0001	0.000	-0.0009	-0.0007
- no favorites	-0.0002	0.0001	0.109	-0.0004	0.0001

Note: number of observations used in the estimation: all events – 59,386 obs., with favorites – 27,516 obs., no favorites – 14, 359 obs.

The results from horse racing markets also support the observation that bettors do not weight probabilities linearly. However, as suggested by the results in the first step, in the case of horse races the behavior of bettors seems to follow a different pattern than in tennis or soccer. Bettors still slightly overweight the small differences between probabilities of winning of horses in events without any strong favorite, yet they overweight the middle-sized differences in probabilities between underdogs and favorites even more. The rationale for this result lies in the higher number of outcomes on the horse race market and thus the lower absolute values of implied probabilities as well as their differences. In such a market structure, unlike the tennis and soccer markets, the implied probabilities never cross the threshold where the underweighting behavior of bettors prevails.

3.6 CONCLUSION

This paper makes several contributions to the literature on decision making under risk and uncertainty. Using an extensive dataset from the world's largest betting exchange, Betfair, I show that bettors bet different amounts on different odds, and that bet size is key to explaining their attitude towards risk. I abandon the assumption of constant bet size commonly used in the literature and provide corrected estimates of the risk preferences of bettors which, indeed, differ significantly from previous studies.

This research also has broader implications for the general analysis of behavior under uncertainty, particularly for discussions regarding the validity of EUT. My results suggest that, when facing a number of outcomes with different winning probabilities, bettors tend to overweight small and underweight large differences in probabilities, which is in direct contradiction to the linear probability weighting function implied by EUT. These findings can be presented as a refinement on Tversky and Kahneman (1992), who report the same behavior of agents with respect to absolute values of probabilities. My results also support the theory of reference points in decision making under uncertainty. However, they indicate that people may use more reference points than the generally accepted 0 and 1, as the outcomes might serve as each other's reference points.

3.7 BIBLIOGRAPHY

Ali, M. M. (1977). Probability and utility estimates for racetrack bettors. *Journal of Political Economy,* Vol. 85 No. 4, pp. 803-815.

Bradley, I. (2003). The representative bettor, bet size, and prospect theory. *Economics Letters,* Vol. 78 No. 3, pp. 409-413.

Forrest, D. and McHale, I. (2007). Anyone for tennis (betting)? *European Journal of Finance,* Vol. 13 No. 8, pp. 751-768.

Gandhi, A. (2007). Rational expectations at the racetrack: Testing expected utility using prediction market prices. *Manuscript, Univ. Wisconsin–Madison*.

Gil, R. and Levitt, S. (2007). Testing the efficiency of markets in the 2002 world cup. *The Journal of Prediction Markets,* Vol. 1 No. 3, pp. 255-270.

Golec, J. and Tamarkin, M. (1998). Bettors love skewness, not risk, at the horse track. *Journal of Political Economy,* Vol. 106 No. 1, pp. 205-225.

Griffith, R. M. (1949). Odds adjustments by American horse-race bettors. *American Journal of Psychology,* Vol. 62 No. 2, pp. 290-294.

Hamid, S., Prakash, A. J., and Smyser, M. W. (1996). Marginal risk aversion and preferences in a betting market. *Applied Economics,* Vol. 28 No. 3, pp. 371-376.

Jullien, B. and Salanie, B. (2000). Estimating preferences under risk: The case of racetrack bettors. *Journal of Political Economy,* Vol. 108 No. 3, pp. 503-530.

Kanto, A. J., Rosenqvist, G., and Suvas, A. (1992). On utility function estimation of racetrack bettors. *Journal of Economic Psychology,* Vol. 13 No. 3, pp. 491-498.

Quiggin, J. (1982). A theory of anticipated utility. *Journal of Economic Behavior and Organization,* Vol. 3 No. 4, pp. 323-343.

Smith, M. A., Paton, D., and Williams, L. V. (2006). Market efficiency in person-to-person betting. *Economica,* Vol. 73 No. 292, pp. 673–689.

Snowberg, E. and Wolfers, J. (2010). Explaining the favorite-longshot bias: Is it risk-love or misperceptions? *Journal of Political Economy,* Vol. 118 No. 4, pp. 723-746.

Tversky, A. and Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty,* Vol. 5 No. 4, pp. 297-323.

Weitzman, M. (1965). Utility analysis and group behavior: An empirical study. *Journal of Political Economy,* Vol. 73 No. 1, pp. 18-26.

3.8 APPENDIX

I assume that bookmakers and traders act as risk-neutral agents and that their orders are larger than the orders of common bettors.[15] On the other hand, common bettors who just choose the outcome mostly place back market orders. As the first two types of bettors are risk neutral, the estimates will be driven by the risk preferences of the common bettors, and will be biased towards risk neutrality. I assume that all common bettors are placing back bets, i.e., betting that a particular player will win, and that matching of the bets is done mostly by bookmakers who stand outside the model. Nevertheless, on real betting exchanges the common bettors can be observed on both sides of the market. In further text I analyze the effect of the simplifying assumption on the validity of the results.

Let us assume that proportion *m* of all bets are backs and *1-m* are lays. Given the total number of bets on a favorite (N_F) and an underdog (N_U) I can compute the corresponding number of backs (B_F and B_U) and lays (L_F and L_U) as

$$\# B_F = mN_F \quad \# L_F = (1-m)N_F$$
$$\# B_U = mN_U \quad \# L_U = (1-m)N_U$$

Because there are only two players and I assume that odds O_F and O_U are fair, it holds that $O_F = \frac{O_U}{O_U - 1}$ and $R_F = \frac{1}{R_U}$. Thus, I can express the cross-relations between the average back bet (B_F, B_U) and lay bet (L_F, L_U) on the favorite and the underdog, respectively, as

$$L_F = B_U(O_U - 1) \;\; L_U = B_F(O_F - 1)$$

Total matched volumes on the favorite and the underdog (VOL_F, VOL_U) are equal to

$$VOL_F = VOL_{BF} + VOL_{LF} = \# B_F B_F + \# L_F L_F = mN_F B_F + (1-m)N_F L_F =$$
$$= mN_F B_F + (1-m)N_F B_U(O_U - 1)$$
$$VOL_U = VOL_{BU} + VOL_{LU} = \# B_U B_U + \# L_U L_U = mN_U B_U + (1-m)N_U L_U =$$
$$= mN_U B_U + (1-m)N_U B_F(O_F - 1)$$

Solving for B_F and B_U gives

---

[15] On Betfair, the volume of a lay order is defined not as the liability of a lay bettor, but as his profit which equals the stake of the bettor on the back side of the trade.

$$B_F = \frac{(1-m)N_F(O_U-1)VOL_U - mN_U VOL_F}{N_F N_U(1-2m)}$$

$$B_U = \frac{(1-m)N_U(O_F-1)VOL_F - mN_F VOL_U}{N_F N_U(1-2m)}$$

I am interested in how the average back bet size changes with a different proportion of backing bettors on the market. Taking derivatives of B_F and B_U with respect to *m* I get

$$\frac{\partial B_F}{\partial m} = \frac{N_F(O_U-1)VOL_U - N_U VOL_F}{N_F N_U(1-2m)^2}$$

$$\frac{\partial B_U}{\partial m} = \frac{N_U(O_F-1)VOL_F - N_F VOL_U}{N_F N_U(1-2m)^2}$$

$$\frac{\partial B_F}{\partial m} > 0 \Leftrightarrow (O_U-1) > \frac{N_U}{N_F}\frac{VOL_F}{VOL_U} = \frac{\frac{VOL_F}{N_F}}{\frac{VOL_U}{N_U}} = \frac{B_F^{comp}}{B_U^{comp}}$$

$$\frac{\partial B_U}{\partial m} > 0 \Leftrightarrow (O_F-1) > \frac{N_F}{N_U}\frac{VOL_U}{VOL_F} = \frac{\frac{VOL_U}{N_U}}{\frac{VOL_F}{N_F}} = \frac{B_U^{comp}}{B_F^{comp}}$$

where $B_F^{comp} = \frac{VOL_F}{N_F}$ and $B_U^{comp} = \frac{VOL_U}{N_U}$ denote the average back bet sizes under the assumption that *m = 1*, i.e., that all bettors are backing, which I used in my estimates.

B_F *and* B_U are continuous on the range of $m \in \langle 0.5; 1\rangle$. Therefore if If $m > 0.5$ and the results of my estimation suggest that the bettors are risk averse, the following inequalities hold:[16]

$$\frac{B_F^{comp}}{B_U^{comp}} < \frac{p_F}{p_U} = \frac{1-p_U}{p_U} = (O_U-1)$$

$$(O_U-1) > \frac{B_F^{comp}}{B_U^{comp}} \Rightarrow \frac{\partial B_F}{\partial m} > 0 \xRightarrow[if\ m>0.5]{} B_F < B_F^{comp}$$

$$\frac{B_U^{comp}}{B_F^{comp}} > \frac{p_U}{p_F} = \frac{1-p_F}{p_F} = (O_F-1)$$

$$(O_F-1) < \frac{B_U^{comp}}{B_F^{comp}} \Rightarrow \frac{\partial B_U}{\partial m} < 0 \xRightarrow[if\ m>0.5]{} B_U > B_U^{comp}$$

Combining the fact that $B_F < B_F^{comp}$ and $B_U > B_U^{comp}$ results in inequality

$$\frac{B_F}{B_U} < \frac{B_F^{comp}}{B_U^{comp}} < \frac{p_F}{p_U}$$

[16] Within the utilized CARA utility framework, the ratio of bets of a risk-neutral bettor satisfies the condition $\frac{B_F}{B_U} = \frac{p_F}{p_U}$.

means that use of the right average back bet size would lead to an even higher risk aversion estimate. Similarly, if the results suggest that the marginal bettor is risk loving, I can reiterate the previous analysis as follows:

$$\frac{B_F^{comp}}{B_U^{comp}} > \frac{p_F}{p_U} = \frac{1-p_U}{p_U} = (O_U - 1)$$

$$(O_U - 1) < \frac{B_F^{comp}}{B_U^{comp}} \Rightarrow \frac{\partial B_F}{\partial m} < 0 \xRightarrow[if\ m>0.5]{} B_F > B_F^{comp}$$

$$\frac{B_U^{comp}}{B_F^{comp}} < \frac{p_U}{p_F} = \frac{1-p_F}{p_F} = (O_F - 1)$$

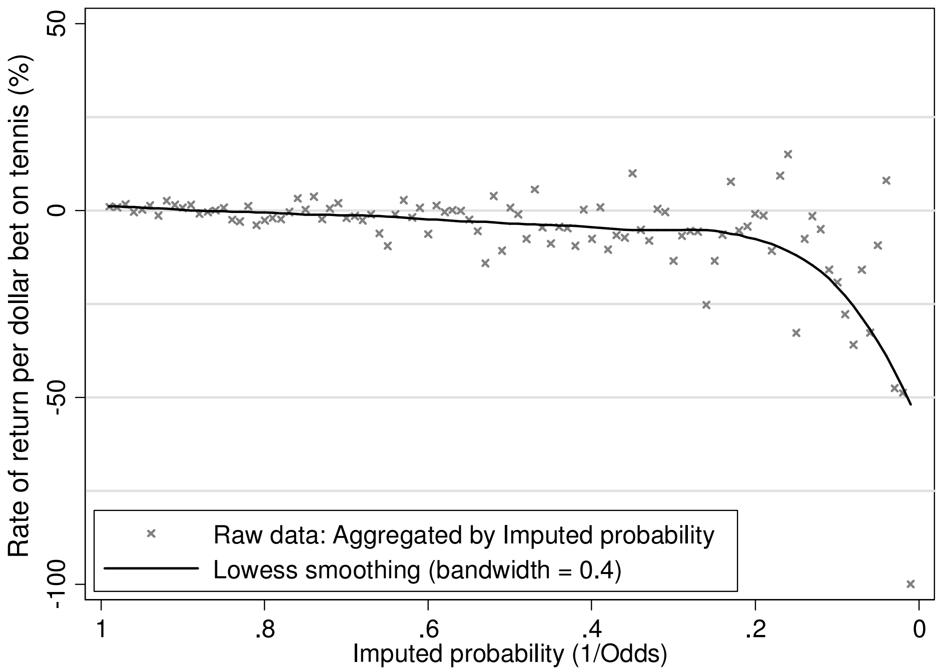
$$(O_F - 1) > \frac{B_U^{comp}}{B_F^{comp}} \Rightarrow \frac{\partial B_U}{\partial m} > 0 \xRightarrow[if\ m>0.5]{} B_U < B_U^{comp}$$

$$\frac{B_F}{B_U} > \frac{B_F^{comp}}{B_U^{comp}} > \frac{p_F}{p_U}$$

In both cases, use of average betting size computed under the assumption that *m = 1* biases the results towards risk-neutral preferences. Thus, as long as the real proportion of common bettors on the back side of the market is higher than 0.5, it is reasonable to conclude that my estimate of risk aversion/risk love is a lower/upper bound of a real value.

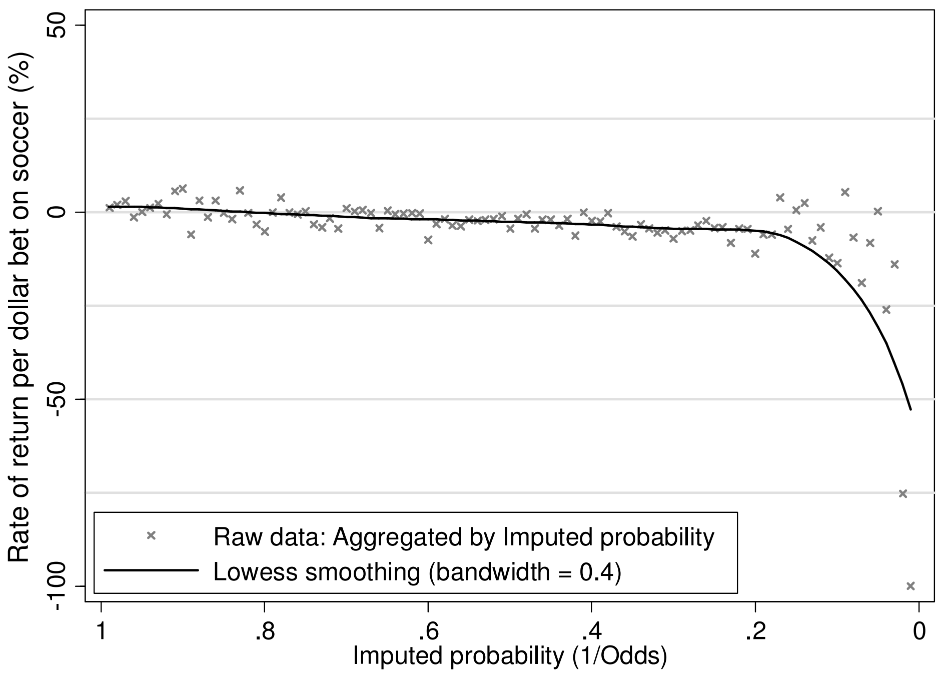
I have also performed an empirical check of my assumptions through the analysis of bets on 60 markets of the 2006 soccer World Cup for which I have available information on the number of back and lay bets. According to this data, the share of "backers" on the market orders is larger than the share of "layers". The share of back bets ranges from 60% to 90% with an average 73% share of all observed bets for 180 outcomes (3 outcomes per market) of match winner markets, and ranges from 60% to 96% with an average 86% share of all observed bets for 1020 outcomes (17 outcomes per market) of the correct score markets. The average lay bet sizes are always remarkably larger than the average back bet sizes.

Figure 3.6: Expected return per dollar bet on tennis at Betfair



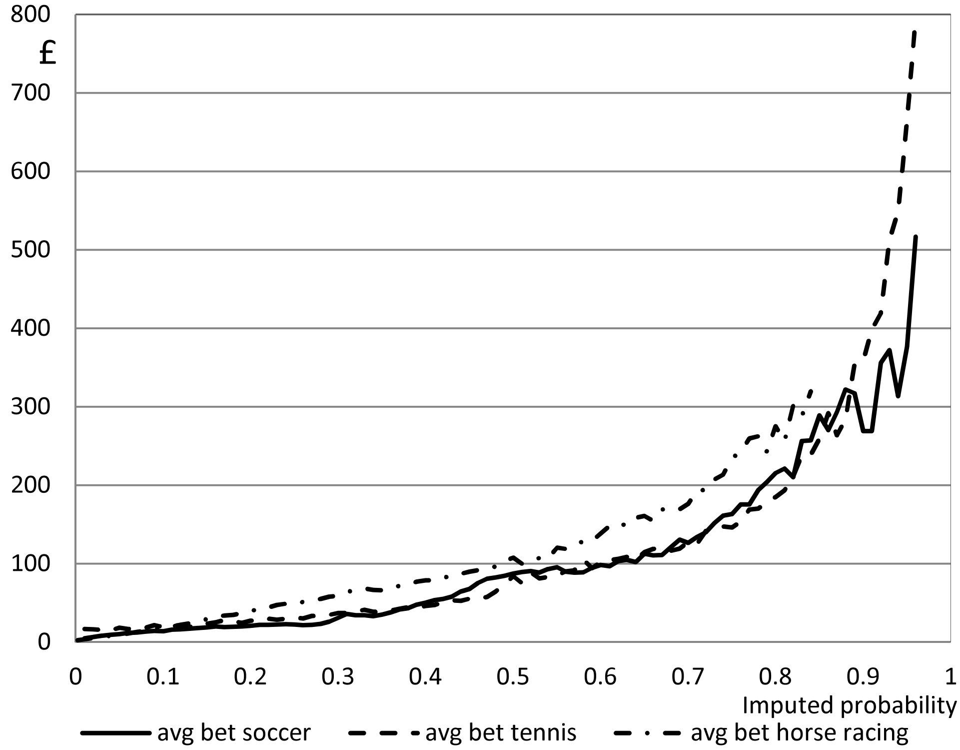
Note: number of observations used: 17,371.

Figure 3.7: Expected return per Dollar Bet on Soccer at Betfair



Note: number of observations used: 70,831.

Figure 3.8: Average bet size at Betfair with respect to imputed probability



Note: number of observations used: tennis – 17, 371 obs., soccer – 70, 831 obs., horse races – 59, 386 obs.