Using Agent-Based Modeling to Explore the Dynamics of Financial Markets and the Potential for Regulation

Björn-Christopher Witte

Für Charlotte Kaufhold

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Cumulative dissertation by

Björn-Christopher Witte

M.A. European Economic Studies

M.Sc. Information Systems

University of Bamberg, Department of Economics

Contact:

Björn-Christopher Witte

Lindemannstr. 27

D-82327 Tutzing

Germany

b.christopher.witte@gmail.com

“Using Agent-Based Modeling
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Björn-Christopher Witte

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CONTENTS

A

Synopsis

1. INTRODUCTION

If there is one group which can benefit from a financial crisis like the one that struck the world in 2008, it may be economic scientists for whom a bulk of unsolved problems suddenly opened up longing to be solved. However, the impact of the crisis affected economic research itself. Scientists were suddenly subject to critique as they seemed to be unable to predict the economic meltdown or to agree on remedies. This critique often points to a sharp dissonance between traditional economic models, associated with the analysis of static equilibria and rational agents, and the contemporary financial system, which appears to be highly dynamic and governed by emotions and heterogonous beliefs. Mark Buchanan, a science writer based in Cambridge, UK, comments on that:

> *"Economists can get reasonably good insights by assuming that human behaviour leads to stable, self- regulating markets, with the prices of stocks, houses and other things never departing too far from equilibrium. But 'stability' is a word few would use to describe the chaotic markets of the past few years, when complex, nonlinear feedbacks fuelled the boom and bust of the dot-com and housing bubbles, and when banks took extreme risks in pursuit of ever higher profits."* (Buchanan, 2009, p. 680)

The conflict of traditional models calls for new approaches which allow for the particular properties of financial markets and facilitate a deeper understanding of financial dynamics. Agent-based modeling (survey by Tesfatsion & Judd, 2006, i.a.) represents such an approach. Agent-based models of financial markets (surveys by LeBaron, 2006; Hommes, 2006) simulate financial markets by replicating the behavior of individual agents and their interaction. They enable the implementation of findings from the field of behavioral finance and, thus, can account for irrational motives.

The present cumulative dissertation comprises five contributions. All studies have three properties in common:

- The research object is a financial market.
- (Computer) simulations of an agent-based model represent the central research method.
- The research question relates to the behavior of the financial (model) market as a whole.

The contributions can be outlined as follows:

- Contribution 1 investigates the influence of the frequency of the publication of fundamental information on market dynamics and efficiency. Basic insights are gained by an algebraic analysis. Then, a simple agent-based model is developed in which the publication frequency represent the independent variable.
- Contribution 2 stress tests the results of Contribution 1 and extends them. To this end, we investigate three existing financial market models and implement a new mechanism of fundamental publication. The simulations uncover some effects which are sensitive to the model setup and some which are robust across models.
- Contribution 3, analyzes the influence of competitive conditions on the risk-preference of agents. As a practical example, the professional competition between fund-managers is considered. An analytical part is followed by an evolutionary model that is based on genetic programming.
- In Contribution 4, a model is developed in which intelligent agents are able to identify systematic patterns in prices and to exploit them. Artificial intelligence is achieved by means of an Artificial Neuronal Network.
- Contribution 5 has been created on behalf of the Bank of England. The model investigates the influence of high frequency trading on market dynamics. To replicate a realistic market infrastructure, trading is done via a double order book. The model is fitted to the equity of Lloyds Plc.

The remainder of this dissertation is organized as follows. Section 2 introduces the common theoretical background of the research projects. Section 3 provides an overview of the research methods applied. Beyond agent-based modeling, these are Genetic Programming and Artificial Neuronal Networks. Section 4 summarizes the singular projects, including the research problems, their analytical approach and the results obtained. Section 5 presents some general conclusions from my research and highlights needs for future work. The original versions of the papers and articles of this dissertation can be found in part B. Part C comprises information about the publication of the Contributions and supplementary documents.

2. THEORETICAL BACKGROUND

Agent-based modeling of financial markets represents the scientific field of this dissertation. This section seeks to produce a more profound understanding of the field by putting it in the context of some other, more fundamental theoretical approaches and concepts it is densely interwoven with. Theories of generic systems serve as a fundamental framework to interpret financial markets and models (Section 2.1). Research problems and their solution though modeling methods are schematized in terms of the Concept of Model-Based Examination by Ferstl (1979) and Ferstl & Sinz (2006) (Section 2.2). Both the theory of systems and the Concept of Model-Based Examination allow for the introduction of some concepts and relationships which are essential for agent-based modeling of financial markets. This field is then interpreted as a combination of its research object, financial markets (Section 2.3), and its research method, the simulation of agent-based models (Section 2.4). Lastly, the field itself is presented (Section 2.5).

2.1 Fundamentals from System Theory

Financial markets and agent-based models can be interpreted as systems. As such, they are subject to theories of generic systems as proposed by Forrester (1961, 1968) and Mesarovic & Takahara (1975).[1] The remainder of Section 2 will clarify this. Interpreting financial markets and models against the background of general systems expands a semantic framework in which some important concepts in the context of the agent-based modeling of financial markets can be introduced.

Formally, a general system, S_G, can be defined as:

$$S_G = \{K, R_G\}. \tag{1}$$

Here, $K = \{K_i \mid i \in I\}$, and each K_i is termed 'system component'. R_G is some non-empty relation over the Cartesian product $K_i, i \in I$. (Ferstl, 1979, p. 11, in reference to Mesarovic & Takahara, 1975). The idea of the formal definition can be expressed as follows: "A system is a collection of parts that interact with one another to function as a whole. However, a system is more than the sum of the parts – it is the product of their interactions". (Maani & Cavana, 2000, p. 6). For each system, a distinction can be made between the system structure and the system behavior. The structure of the system corresponds to the set $\{K_i \; x \; K_j \mid i, j \in I \wedge i \neq j\}$. In other words, the system structure is constituted by the elements of the system and the relationships between them. In contrast, the system behavior is defined as the relation $R_G \subset \mathrm{X}\,(i \in I)\,K_i$, where R_G is some non-empty relation over the Cartesian product $K_i, i \in I$ (Ferstl, 1979, p. 11). In other words, the system behavior equals the set of transitions between

[1] Please be aware that I do not intend to refer to the comprehensive field of Systems Theory (in German: "Allgemeine Systemtheorie") (Bertalanffy, 1950, i.a.). Rather, I select some theoretical approaches on generic systems which are appropriate to introduce relevant concepts in the context of the present dissertation.

different states of the system over time, with the state of the system being equal to the set of values of the variables of the system components. System behavior and system structure are strongly interdependent, since "any specified behavior must be produced by a combination of interacting components" (Forrester, 1982, p. 4-1). Both concepts can reveal various degrees of complexity. Complexity of structure can be understood as the number and heterogeneity of system elements and relationships, whereas, complexity of behavior refers to the variety of possible behavioral patterns of the system and their variability over time.[2] Further, theory distinguishes between static and dynamic systems. A dynamic system is some set

$$S_D = T, X, Y, Z, R_D, \tag{2}$$

where T is some time set, X is some input set, Y is some output set, Z is some set of system states, and R_D denotes the behavior of the dynamic system. R_D can be specified as the relation $R_D \subset \mathrm{T} \times \mathrm{X} \times \mathrm{Z} \times \mathrm{T} \times \mathrm{Y} \times \mathrm{T} \times \mathrm{Z}$ (Ferstl, 1979, p. 23). The system is static if its behavior can be expressed without making reference to *T*.

The behavior of dynamic systems is often coined by feedback. A feedback system is defined as a system which "is influenced by its own past behavior" (Forrester, 1982, p. 1-5). Feedback occurs if and only if the causal relationships between model components form one or many circles termed "feedback loops". Feedback loops and their interplay may cause immense behavioral complexity of a system even if its structural complexity is relatively low. Feedback, thus, exacerbates the prediction of the behavior of a dynamic system drastically, which may lead to disastrous results when the system needs to be regulated. The theory of System Dynamics (Forrester, 1961; Sterman, 2000) investigates such feedback systems. A third distinction can be made between different system levels. Whereas the 'micro' level embraces the singular system components and their relationships, the 'macro' level refers to properties of the system as a whole.

2.2 A General View on Model-Driven Research

Projects in the field of agent-based modeling of financial markets, seek to solve research problems by constructing models of the research object. The Concept of Model-Based Examination[3] by Ferstl (1979) and Ferstl & Sinz (2006), as displayed in figure 1, represents a

[2] The definitions are derived from the corresponding concepts "complicatedness" (dt.: "Kompliziertheit") and "complexity" (dt.: "Komplexität") by Ulrich & Probst (1991), pp. 57.

[3] in German: "Modellgestützte Untersuchungssituation".

general scheme of investigations of this kind. The scheme illustrates steps in the research process, and may help to elucidate motives for the use of models.

The scheme can be read as follows. Any research project starts with a research goal (U_S) which relates to some research object (S). In conjunction, the research goal and the research object define the research problem (P_O). To obtain results for U_S, a research method is needed, which operates on S. In the present dissertation, the research objects are financial markets. The corresponding research questions relate to aspects of behavior on the macro level. Example: "Can a firm stabilize the dynamics of its equity by disseminating fundamental information less often?" (see Contribution 1). U_S, S and the examination results to be gained represent parts of the level of the original system. In model-based research, another system is created which maps the level of the original system artificially: the level of the model system.

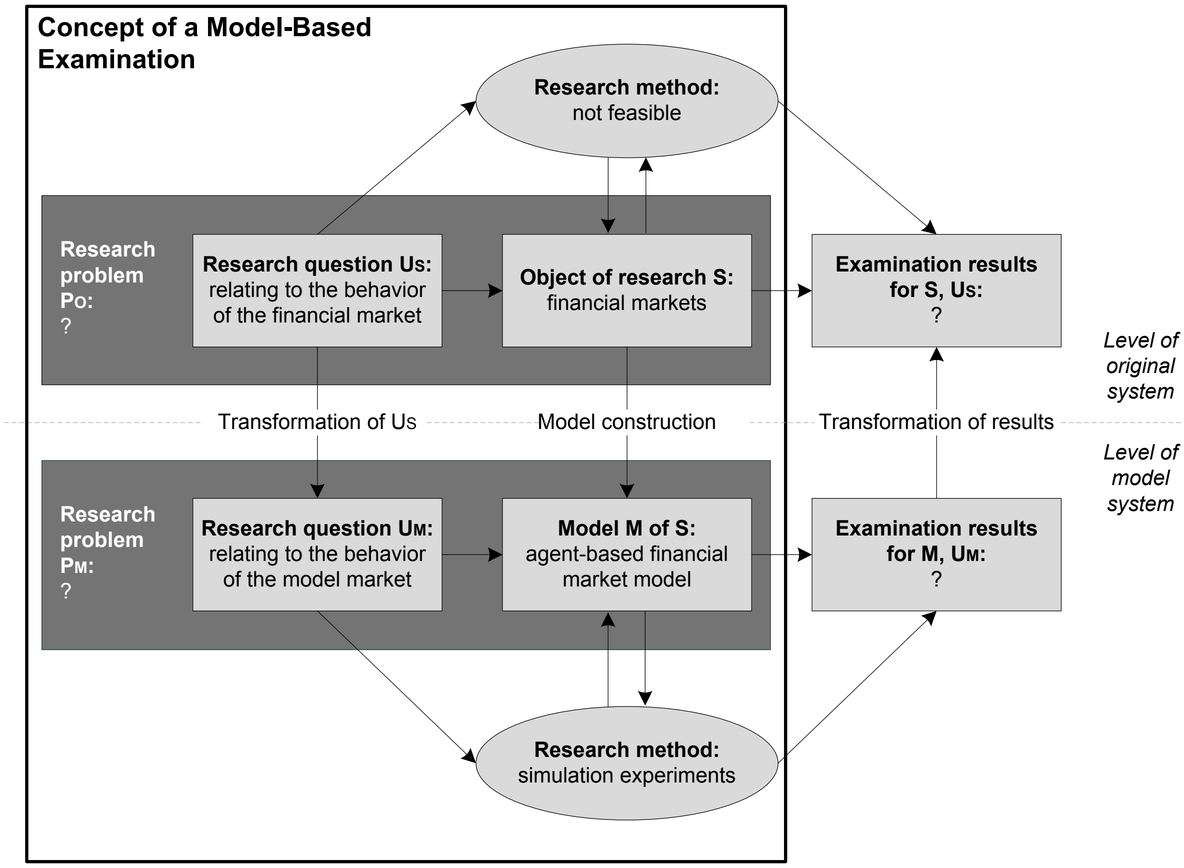

Figure 1: The Concept of Model-Based Examination**.**

The reason for constructing a model is the absence of a viable research method for P_O. Impediments can be monetary costs or effort to gain data, risk of experiments, or sheer impossibility, e.g. when the research object is not observable. For research in financial markets, many of these obstacles may apply. For example, testing regulative measures, such as changes of publication frequency, may involve substantial costs and risks if done in a real market. Further, the behavior of the real market may be too complex to isolate relevant mechanisms from interferences. The model, defined as “some system that is a goal-oriented representation of another system” (Ferstl & Sinz 2006, p. 20), reduces the structural complexity of the real market to those components and relationships which appear to be relevant for the research problem. Technically, a model, *M*, corresponds to a 3-tuple with:

$$M = (S_O, S_M, f). \tag{3}$$

Here, S_O stands for the system to be modeled with the set of system components V_O; S_M is some model system with the set of system components V_M; and $f: V_O \to V_m$ is some model representation (Ferstl & Sinz, 2006, p. 20). Although the Concept of Model-Based Examination displays the step of model construction as a one-directional relation, the model construction is often reciprocal and iterative. In the process of model construction, the model structure is successively adapted to replicate relevant criteria of the structure and/or the behavior of the original system. The testing of the fit between model and original system is termed as ‘validation’. The degree of this fit is denoted as ‘accuracy’. Accuracy and validation can refer to system structure or to system behavior.

On the level of the model system, a viable research method may be feasible. For the present dissertation, this method is simulation. Simulation can be defined as “a numerical technique for conducting experiments with certain types of mathematical models which describe the behavior of a complex system on a digital computer over extended periods of time” (Naylor, 1971, p. 2). Before simulations are conducted, the research question U_S has to be reformulated so that it refers to variables of the model, which produces the research question U_M. Together, U_M and *M* constitute the research problem on the model level (U_M). Operating on the model system, the method of simulation yields the examination results with reference to the model (M) and the research goal on the model level (U_M). The final step is the transformation of these results back to the level of the original system. To guarantee that insights gained on the model level are also valid for the original system, a high degree of accuracy of the model is important. The goal of accuracy rivals with the goal of keeping the model as tractable as possible. As a result, the modeler has to compromise between (structural and behavioral) accuracy and structural simplicity. Mandelbrot (1997) condenses this requirement for the models of financial markets as such:

"A good model of price variation is one that mimics a great number of empirical regularities within a simple framework".

(Mandelbrot, 1997, referenced by Westerhoff, 2003, p. 246)

2.3 Financial Markets

Financial markets represent the research object of the projects in this dissertation. Financial markets can be defined as "intermediaries between suppliers and users of funds, that is, between lenders and borrowers". Traded funds embrace stocks (stock markets), foreign currencies (foreign exchange markets), and other financial securities (Shim & Siegel, 1995). In a broader understanding, the financial market also embraces these lenders and borrowers, i.e., the agents trading. By interpreting financial markets as systems, the financial market can be portrayed by the dimensions of generic systems. Friedrich (1984) outlines eighteen antagonistic criteria and respective attributes of generic systems. Here, I select two of them to highlight important aspects of financial markets.

First, financial markets are dynamic. In a dynamic system, as defined by eq. 2, there is at least one relationship (function) between system variables that involves variable values of different moments of time. Differential equations or difference equations capture these relationships algebraically. In a financial market, a central relationship of this kind is established when computing price trends. Price trends necessarily result from levels of prices at different moments of time.[4] Further, by representing a crucial determinant of technical trading (Murphy, 1999; Pring, 2002; Edwards et al., 2007), price trends constitute an important component of the financial market system.

Second, financial markets are complex. Johnson et al. (2003, p. 3−4.) list several properties which characterize complex systems. Four of them will be focused which apply to financial markets very well:

- *Non-stationarity*: Statistical or dynamical properties observed in the past may not persist in the future. Volatility clustering (Mandelbrot, 1963, and followers) is an observation which illustrates this property for financial markets. Volatility clustering refers to the alteration of calm and turbulent intervals of price volatility. The system switches between different patterns of behavior.

[4] A common form to capture price trends is to compute moving averages. The moving average illustrates the involvement of prices from different moments of time: $Trend_t = \alpha * Trend_{t-1} + (1-\alpha)(P_t - P_{t-1})$. Here, α represents a memory parameter ($0 < \alpha < 1$) and P_t stands for the price in time *t*.

- *Many interacting agents*: The system is composed of a multitude of heterogeneous agents that interact with each other. In a financial market, such as a stock exchange, large numbers of investors interacts with each other by means of communication and financial transactions. Heterogeneity between investors is given in terms of their beliefs about market development ('heterogenous beliefs') and in terms of the variety of trading strategies they rely on.
- *Evolution*: A system is evolutionary if its components or their properties change over time (Friedrich, 1984, p. 47). In a financial market traders may adapt their behavior as they learn from experience. Evolution further applies to the kind of traders. Whereas about four decades ago[5], trades were based on the incentive of human beings, today, a great share of trading volume is performed by computers.[6] According to Johnson et al. (2003), evolution also implies the presence of extreme behavior, i.e., the dynamics of the system may evolve far from equilibrium and tend to show vigorous motions. Bubbles and crashes may be regarded as examples for extreme behavior in financial markets.
- *Open system*: An open system can be defined as a system that interacts with its environment (Ferstl, 1979, p. 27). For a system which is densely interwoven with its environment, it is difficult to tell if the cause of a certain macro behavior is endogenous (within the system boundaries) or exogenous (beyond the system boundaries). Movements of financial prices illustrate this property, as the degree to which a change of prices is caused by economic news (exogeneous cause) or merely by investor sentiment (endogenous cause) is often unclear.[7]

The complexity of the behavior of financial markets is constituted by a set of statistical properties, often denoted as 'stylized facts', which are typical for financial dynamics. For overviews see Cont, 2001; Johnson et al., 2003; Sornette, 2003; Lux 2009; and Chen, 2009. Five of the most important stylized facts will be introduced briefly:

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[5] In 1971, the National Association of Securities Dealers Automated Quotations (NASDAQ), was founded as the first electronic stock market. Due to the digitalization of the trading platform, a complete automation of the trading process, termed 'algorithmic trading', became possible and began to spread across markets.

[6] Brogaard (2010) reports that in 2010, more than two-thirds of the turn-over on the US equity market was due to computers which are able to trade several thousand times a second ('High Frequency Trading'). Contribution 5 investigates this fundamental change of trading in detail.

[7] Analyses of the 'flash crash', such as Kirilenko (2011), are examples of recent research in which this degree should be found.

- *Bubbles and crashes*: Prices disconnect from the intrinsic value of the underlying asset for a significant span of time ('bubble') before quickly readjusting ('crash'). Rosser (1997) surveys empirical research on this phenomenon.
- *Excess volatility*: Prices move more strongly and/or more often than necessary in order to incorporate all fundamental news (surveys by Fama, 1981, 1998; Cochrane, 1991; Shiller, 1990, 1992, 2003).
- *Uncorrelated returns*: The dynamics of prices do not show any significant autocorrelations (Fama, 1965, and followers). This property complies with the view that financial markets are unpredictable. However, uncorrelated returns do not prove unpredictability, as systematic patterns might be too complex to be reflected in autocorrelations (Contribution 4 focuses on this issue in detail).
- *Volatility clustering*: Intervals in which price volatility is tranquil alternate with intervals of turbulence (Mandelbrot, 1963, and followers). Volatility clustering can be interpreted as a product of 'long memory' in financial time series (Greene & Feelitz, 1977; Ding et al. 1993; Lobato & Savin, 1998). Long memory refers to the fact that the behavior of the market at some time is influenced by its behavior a "long" time ago.
- *Heavy tails*: The share of observations at the ends of the distribution of returns is significantly greater than with a normal distribution of equal mean and equal variance. (See Mandelbrot, 1963, and followers). Heavy tails are regarded as a product of power laws in financial dynamics (Gabaix et al., 2003; Lux, 2006).

Findings of bubbles and crashes and excess volatility challenge the belief that financial markets are efficient.[8] A market is efficient if the price reflects all information that are relevant for the value of the underlying asset (or at least all information publicly available) at all times (The introduction of Contribution 1 surveys definitions of market efficiency in more detail). Further, the stylized facts suggest that the dynamics of prices is not only driven by exogenous news but also endogenously by the interaction of traders whose behavior disaccords with the 'homo-oeconomicus' concept.

[8] Critique of findings of this kind points to the so-called "joint-hypothesis problem" (Fama, 1991, i.a.): To evaluate if prices reflect value, assumptions about the true intrinsic value are required. As a result, respective findings might merely indicate that the model of the intrinsic value does not account for all variables relevant for investors.

2.4 Agent-Based Modeling

Agent-based modeling (standard volumes by Gilbert & Troitzsch, 2005; Tesfatsion & Judd, 2006; and Gilbert, 2008) represents a technique of model development. Bonabeau (2002) formulates the essence of agent-based modeling as follows: "In agent-based modeling (ABM), a system is modeled as a collection of autonomous decision-making entities called agents."[9] The research method operating on an agent-based model is simulation. Apart from a few exceptions, the simulations are run by computers.[10] Figure 2 proposes a way of illustrating the ABM approach.

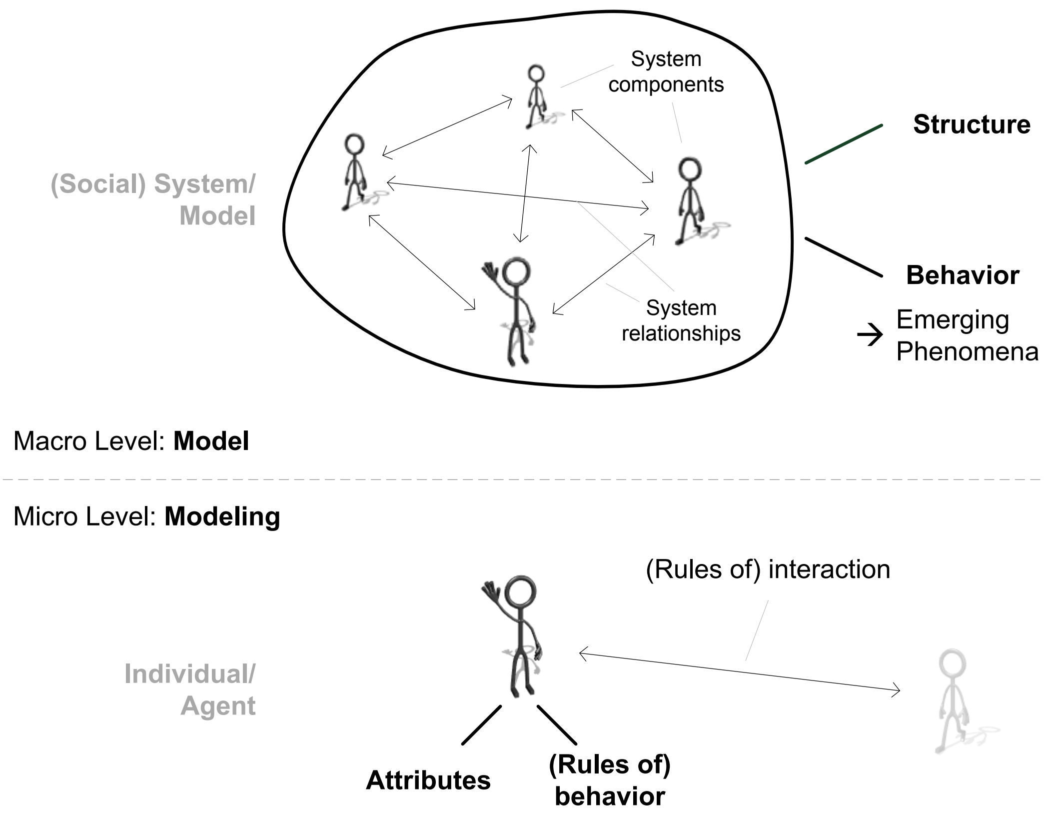

Figure 2: The ABM approach illustrated. Own creation.

The figure can be read as follows. By definition, ABM aims to reproduce the agents the original system is composed of in a technical way. This implies modeling is to be done on the micro level. The reproduction of agents comprises the definition of their attributes and the rules of behavior they adhere to. Further, rules of interaction may be established, such as ways

[9] Note that a "decision making entity" must not necessarily be human, but agents might be equal to organizations or machines. An example is given in Contribution 5 in which agents are computers.

[10] The most prominent exception might be the famous segregation model by Thomas Schelling (Schelling, 1969, 1971). Constructing one of the first agent-based models, Schelling investigated spatial segregation between black and white city residents in the US by means of a checkerboard framework and simplistic rules of movement.

of communication. In all, the agents and their relationships constitute the model as a whole, i.e., the macro level. Since the model represents a system, model structure and model behavior can be distinguished. The model structure is constituted by the agents, being the system components, and the relationships between them. These relationships may but do not have to be given by the rules of interaction; agents could be interacting indirectly with each other, for example by influencing global variables, such as stock prices, which vice versa influence the behavior of agents. In contrast to the model structure, the model behavior might be extremely difficult to deduce analytically. In fact, through the interplay of feedback loops, the model behavior can be significantly more complex than the behavior of individual agents. This implies the model behavior possesses properties which are not equal to the properties of agents. Properties of the model behavior which arise due to the interaction of agents are denoted as 'emergent phenomena'. Darley (1994) describes an emergent phenomenon as a "large scale, group behavior of a system, which doesn't seem to have any clear explanation in terms of the system's constituent parts."

According to Bonabeau (2002), the advantages of ABM in comparison to other modeling techniques are threefold: "(i) ABM captures emergent phenomena; (ii) ABM provides a natural description of a system; and (iii) ABM is flexible. It is clear, however, that the ability of ABM to deal with emergent phenomena is what drives the other benefits." The benefits mentioned can be explicated as follows:

(i) *Capturing emergent phenomena*: Emergent phenomena are often easily observable; however, identifying the micro processes by which they are caused can be difficult. ABM allows implementing relationships on the micro level and simulating the macro behavior they produce. In this way, ABM can be used for the explanation of emergent phenomena and, thus, to improve our understanding of complex agent-based systems.

(ii) *Flexibility*: An agent-based model can be adapted in a variety of dimensions. It is relatively easy to alter model parameters (e.g. the number of agents), to change the aggregation level (e.g. by aggregating individuals to groups), or to change the model structure (e.g. by modifying the rules of behavior). This facilitates adjusting the model to new research questions or to changes of the system modeled.

(iii) *Natural description*: If the system to be modeled is constituted by interacting agents, the most straightforward way of modeling the system is to reproduce the agents and their behavior. As a benefit, the resulting model will appear close to reality and the effort required to map the original system to the model and vice versa is little.

The facts on ABM presented so far can be used to deduce conditions for research problems under which ABM is promising. These conditions are:

(1) The original system consists of autonomous decision-making entities which interact with each other.
(2) Information about the behavior of agents and their interaction is existent to a sufficient extent.
(3) The behavior of the original system is complex.
(4) The complexity of behavior is presumed to be due to the interaction of agents.
(5) Relevant research questions aim at clarifying the relation between the interaction of agents and the system behavior.

2.5 Agent-Based Modeling of Financial Markets

ABM of financial markets (surveys by Hommes, 2006, and LeBaron, 2006) can be understood as the application of the research method, computer simulations of agent-based models, to the research object, financial markets. The field should be introduced by commenting on its potential and the state of research, the role of behavioral finance, the method of model validation, and dimensions to distinguish between models.

2.5.1 Potential and State of Research

From the facts on financial markets (Section 2.3) and the facts on ABM (Section 2.4), the potential of using ABM for the exploration of financial markets is easy to see. Section 2.3 has shown that financial markets are complex dynamic systems consisting of many heterogeneous agents in interaction with each other. The complexity of the behavior of financial markets, such as bubbles and crashes, can be hypothesized to be due to the interaction of traders. However, the precise relation between micro structure and macro behavior is difficult to deduce analytically. Section 2.4 has found that systems with the properties mentioned are well-suited to the application of ABM. ABM highlights the micro causes of emergent phenomena and thus has great potential to improve our understanding of financial dynamics.

In fact, beginning with the pioneer works in the early 1980s[11], ABM has proven to be a fruitful tool for financial market research. Two major fields of application can be identified. First, ABM is employed to explain the stylized facts of financial markets, such as volatility

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[11] Beja & Goldman (1980) is regarded as one of the first agent-based models of a financial market. In a very simple framework, the authors analyze market stability in dependence of the behavior of fundamental and technical traders.

clustering (e.g. Lux, 2000; Gaunersdorfer & Hommes 2007; see Cont, 2007, for a survey) or bubbles and crashes (e.g. Levy et al. 2000; Boswijk, et. al., 2007; de Jong et al. 2007). Second, the agent-based models can be used as artificial laboratories. One goal in this field is to gain insights into the performance of trading strategies or their influence on market dynamics (e.g. Beja & Goldmann, 1980; deLong, 1990a, b; Chiarella et al., 2006; see also Contribution 5). Another goal is to explore regulative measures for the improvement of market efficiency (Westerhoff, 2008, surveys models in this field). Examples are transaction taxes (Westerhoff, 2003a; Dieci & Westerhoff 2006); central bank interventions (Szpiro, 1994, Westerhoff, 2001, Westerhoff & Wieland 2004, Wieland & Westerhoff, Reitz et al. 2006), trading halts (Westerhoff 2003b, 2006), publication policies (see Contribution 1 and 2), and the Basel II convention (Hermsen, 2010).

Typically, the behavior of agent-based models of financial markets is chaotic, complex and continuously out of equilibrium. This way, agent-based models often mimic real financial markets more accurately than traditional models. One of the weightiest insights produced by ABM of financial markets might be the notion that some of the most important stylized facts of financial markets can emerge from the interaction of boundedly rational agents. This insight challenges the traditional view of efficient markets in which the stylized facts are assumed to be originated by economic fundamentals.

2.5.2 Behavioral Finance

As mentioned in Section 2.4, ABM requires information about the behavior of the agents of the original system. ABM of financial markets obtains a significant part of this information from the scientific field of behavioral finance (see Shleifer, 2000, and Hirshleiver, 2001, for surveys on the field). In contrast to the informed and rational homo oeconomicus, behavioral finance stresses the cognitive limitations of economic agents. The focus is descriptive since the field examines how economic agents really act rather than how they should act. According to Shleifer (2000), behavioral finance is built on two pillars: investor sentiment and limited arbitrage. The notion of investor sentiment is based on a large body of experimental research (Simon, 1955; Kahneman et al., 1982; Smith, 1991) which states that economic agents act in a boundedly rational manner. Bounded rationality implies that economic agents lack the computational power to derive fully optimal actions from the information they receive. Moreover, they succumb to behavioral traps and fallacies of the human mind. Economic agents are unable to estimate probabilities correctly (Kahnemann et al., 1982) and succumb to irrational motivations like regret (Clarke et al., 1994) or greed and fear (Lo et al., 2005). They trade on noise or rumors considered as information (Black, 1986) and show abundant confidence without economic reason (Barber & Odean, 2001; Gervais & Odean, 2001). Other studies indicate inconsistencies in the perception of utility (Kahnemann & Tversky, 1979) and point to the meaning of problem presentation (Benartzi & Thaler, 1995). Yet the economic agents do not err independently from each other, which could level out their failures on average. Instead, investors interact with each other and seek for orientation by observing the behavior of others – a mechanism commonly known as 'herding' (Hubermann & Regev, 2001).

Investors who are subject to investor sentiment tend to drive a gap between the price of an asset and its intrinsic value. The notion of limited arbitrage (see Gromb, & Vayanos, 2010, for a summary of the state of research) clarifies why this gap actually emerges without being closed immediately. Even if a group of traders behaves rationally by trading on the mispricing, their investment volume does not suffice for the entire removal of the distortion.

2.5.3 Model Validation

Section 2.1 has stressed the meaning of model validation, which may be qualitative or quantitative. To validate an agent-based model of a financial market, econometric methods are used. The qualitative validation is typically done by testing the ability of the model to replicate the stylized facts of financial markets. In contrast, the quantitative validation refers to comparisons of measures of financial market dynamics between the model and the real market. Brief descriptions of possible tests of the stylized facts introduced in Section 2.3 should exemplify the step of model validation.

- *Excess volatility*: To test for excess volatility, the volatility of the fundamental value is subtracted from the volatility of prices. The result is denoted as excess volatility. The computation can be done as follows.

  $$V^{ex} = V^P - V^F = \frac{1}{N}\sum_{t=1}^{N}|P_t - P_{t-\Delta t}| - \frac{1}{N}\sum_{t=1}^{N}|F_t - F_{t-\Delta t}|, \qquad (4)$$

  where $V^P(/V^F)$ stands for the volatility of prices (/fundamentals), $P_t(/F_t)$ for the price (/fundamental value) at time *t*, and Δt is the interval of measurements.

- *Uncorrelated returns*: To test for uncorrelated returns, the autocorrelations of returns are computed for different lags, τ. The autocorrelation $R(\tau)$ between the return in *t* and the return in $t-\tau$ is computed as:

  $$R(\tau) = \frac{E[(r_t-\mu)(r_{t-\tau}-\mu))]}{\sigma^2}, \qquad (5)$$

where σ^2 is the variance of the returns in the sample and μ is the sample mean. As a second step, the significance of the autocorrelations needs to be evaluated.

- *Volatility clustering*: The test for volatility clustering is analogue to the one for uncorrelated returns but absolute or squared returns are taken. An alternative is to compute the Hurst coefficient of the return distribution. The Hurst coefficient (Hurst, 1951) captures the degree to which a large observation tends to be followed by another large observation (In contribution 5, the relatively complex computation is explained).
- *Heavy tails*: The fraction of observations in the tails of a distribution is indicated by the tail index. A smaller index corresponds to heavier tails. The Hill estimator, *H*, (description in Lux & Ausloos, 2002) approximates this index. It is defined as follows:

  $$H = \left(\frac{1}{k}\sum_{i=1}^{k}(ln|\Delta p_{L-i+1}| - ln|\Delta p_{L-k}|)\right)^{-1}, \tag{6}$$

  where k denotes the number of observations in the tail. To calculate the index, the returns Δp_t have to be sorted in a descending order: $\Delta p_L > \Delta p_{L-1} > \Delta p_{L-2} > \ldots > \Delta p_1$. Common tail fractions are 3% and 5%.

2.5.4 Dimensions of Models

Agent-based models of financial markets can be classified in a variety of dimensions. To illustrate the range of models in the field and in the present dissertation, four dimensions are addressed in the following:

- *Heterogeneity*. The first dimension is the heterogeneity of agents. Chen (2008) proposes a distinction between 2-type, 3-type, many-type, and autonomous-agent designs. 2-type designs typically follow the fundamentalist-chartist approach (See Contribution 1). The approach is based on the empirical notion that traders in financial markets use two classes of strategies (Taylor & Allen, 1992; Menkhoff, 1997; Lui & Mole, 1998). Fundamentalists seek to derive the intrinsic value of an asset by analyzing fundamental data. The strategy aims at long-term profits through the exploitation of mispricing (For standard volumes on fundamental analysis see Stein, 1988; Greenwald et al., 2001; and Damodaran, 2002). Chartists rely on technical rules of trading. They believe that the dynamics of prices in the past contains information to predict future prices. The strategy aims at short-term profits. (Volumes on technical trading include those by Murphy, 1999; Pring, 2002; and Edwards et al., 2007). The greatest heterogeneity is achieved by autonomous-agent designs (the Santa Fee Artificial Stock market [see Arthur et al., 1997, for an introduction] and related model are examples. See also Contribution 3). Here, agents are not pooled into groups, but every agent can be unique in terms of the value of his attributes and his rules of behavior.

- *Evolution*. Evolution refers to the fact whether agents can change their behavior or not. If evolution is completely absent, any agent sticks to constant rules of behavior which are predefined by the modeler (see Contribution 5). The next level is represented by models which allow agents to switch between several predefined strategies, e.g. under the assumption that the attractiveness of a strategy is determined by its historic profits (see Contribution 4). The most advanced approach is to define the building blocks of strategies only. Here, the combination of these building blocks to trading strategies and/or their parameterization occurs automatically. Popular approaches for the automation of this process are Genetic Programming (see Contribution 3) and Artificial Neuronal Networks (see Contribution 4).
- *Time*. Dynamic models require a conceptualization of time. In the simplest approach, time proceeds in discrete steps (discrete time). Here, time-dependent relationships are represented by difference equations (see Contributions 1, 3 and 4). A more realistic alternative is to use differential equations. This leads to a model whose variables can be computed at arbitrary steps of time (continuous time). The third option is the event-driven approach (see Contribution 5). In event-driven models, the time of events is computed. Events can trigger each other optionally with delays in between (e.g. the arrival of fundamental news may trigger orders by fundamentalists). In contrast to the other two approaches, the simulation of an event-driven model does not require the setting of a time interval in which the model variables are computed.
- *Price setting*. In financial markets, a variety of methods for the determination of prices can be found. The same applies for the respective agent-based models. Here, one of the simplest methods is the market-maker approach (Farmer & Joshi, 2002). The market maker can be interpreted as an intermediary between buyers and sellers who supplies the demand for assets from his own inventory. Further, the market maker adapts prices according to the net demand she observes. Usually, this behavior is formulized in one simple equation (see Contribution 1). The second approach, which is well known from traditional equilibrium models, is based on the computation of equilibrium prices for which the net demand equals zero (see Contribution 4). This approach might be regarded as rather theoretical, as the computation of equilibrium prices is very unusual in real financial markets. Another class of models uses a quite

realistic approach by reproducing a double order book – a popular price mechanism in stock markets (see Contribution 5). Finally, some models assume trading to occur by random encounters of buyers and sellers (e.g. Duffie et al., 2005). A central institution of price setting is absent.

3. RESEARCH METHODS USED IN THE PRESENT DISSERTATION

Computer simulations of agent-based models represent the central research method of this dissertation. Apart from this, two other research methods should be highlighted: Genetic programming, which is used in Contribution 3, and Artificial Neuronal Networks (ANNs), used in Contribution 4.

3.1 Genetic Programming

Genetic algorithms, originated by J.H. Holland (1975), are learning methods which mimic the biological process of evolution. A genetic algorithm creates 'candidate solutions' from a defined set of building blocks, which can be interpreted as genes. Typically, the resulting candidate solutions are not preselected by a defined fitness criterion but prove their fitness in competition with each other. The construction of candidates is based on two genetic operators: crossover and mutation. Crossover refers to the combination of two candidate solutions, the 'parents', to create a 'child'. Typically, the child adopts the genes of each parent to an equal degree. Crossover makes sure that successful building blocks persist over generations. The final genetic code of the child is achieved by modifying some of its genes slightly. This is denoted as mutation. Due to mutation new building blocks enter the population, which maximizes the set of potential candidates.

The technique has considerable advantages. The modeler must not define an initial set of candidates to be evaluated but merely their building blocks. Therefore, less previous knowledge is required. Furthermore, due to the large search space, the quality of the solution finally found is likely to be very high. Due to these features, genetic algorithms have proven to be a successful tool in economic modeling (See Safarzyńska and van den Bergh, 2010, for a survey). Goals of application are, in particular, the derivation of optimal rules of trading and investment (see Potvin et al., 2004, and Lensberg & Schenk-Hoppe, 2007, for recent examples).

3.2 Artificial Neuronal Networks

ANNs are inspired by the human brain which consists in complex webs of densely interconnected neurons. When the aggregate input of a neuron exceeds a certain threshold, the cell ‘fires’ and activates other linked neurons, provided that the stimulus is high enough. Advantages of this design consist in its virtually infinite range of possible representations and its high independency from singular neurons.

Invented by psychologist Frank Rosenblatt in 1958, ANNs replicate the biological structure numerically. Here, neurons are embodied by artificial units spanning a two-dimensional network. In contrast to the biological system, the structure of an ANN is organized in different layers. The first layer is the input layer, whose units each represent a sensor for the value of one independent variable. The last layer is the output layer. The output unit yields the result, that is, the prediction of a dependent variable. Between input and output layer up to two hidden layers with variable number of units are used to be implemented. A higher number of hidden layers and units improves the potential of the network to learn more complex, nonlinear functions but deteriorates the cost of training and the speed of convergence.

In the case of simple perceptron, the state of a unit may either be on or off, whereas in the case of a sigmoid unit, the threshold output is a continuous function of its input. In each case, the aggregate input is computed as the sum of the single inputs each multiplied by a weight factor. The weight factors are decisive for the ANN’s behavior. To represent a certain function, the weight factors have to be learned. To this end, a set of data is divided into three subsets which are either used for training, testing, or validation. A popular method for the learning of the weight factors is the so-called Backpropagation Algorithm. The algorithm takes the network output and compares it to the target value of a set of training examples. The discrepancy indicates the adaption of weight factors needed. Backpropagation denotes the successive retracing of errors which become apparent at the output units to earlier units in order to correct their weights respectively.

ANNs can represent complex relationships between variables, even if the structure of the ANN is relatively simple. Further, ANNs do not require the modeler to know these relationships ex ante. These benefits are very useful for models of financial markets, in which agents should identify systematic relationships between economic variables autonomously.

4. SUMMARY OF CONTRIBUTIONS

This Section provides brief summaries of the contributions of the present dissertation, which include the respective research problem, the analytic approach, and the results obtained.

4.1 Temporal Information Gaps and Market Efficiency: A Dynamic Behavioural Analysis

4.1.1 Research Problem

Institutional regulations determining the frequency with which firms have to publish fundamental reports differ between countries and markets. Further, the firms themselves face some freedom of decision with respect to their publication policy. It can be hypothesized that the publication frequency has some influence on the dynamic properties of the equity price of the firm. However, this relation is still vague. This motivates the research question: How does the frequency of the publication of fundamental news influence financial market dynamics? In particular: Does the dynamics of an equity stabilize or destabilize if the firm disseminates information more/less often?

4.1.2 Analytic Approach

Fundamental news can be interpreted as exogenous shocks for price dynamics, and the entirety of shocks can be understood as exogenous noise. Accounting for this, a preliminary part explores the influence of the publication frequency on the quantitative properties of the exogenous noise. Therefore an algebraic analysis is conducted. A second part explores how the effects established might influence a financial market. To this end, an agent-based model is developed following the fundamentalist-chartists approach. Agents switch between strategies depending on market distortion.

4.1.3 Results

The algebraic analysis shows that a change of the gap between moments of publication has three effects on exogenous noise. Expressed pragmatically, these effects can be summarized as follows: Every quadruplication of the gap will quarter the number of shocks in a finite span of time (i), double the mean size of a shock (ii), and halve the average noise level (iii). The agent-based simulations indicate that the impact of these effects on the dynamics of prices is complex. Longer gaps allow the dynamics to tranquilize. However, the amount of unpublished information tends to rise. The sudden dissemination of the bulk of news can trigger intervals of turbulent volatility. The net result of these effects on indicators of market stability and efficiency is sensitive to the interval in which the gap is altered. These results suggest that an alteration of publication frequency in reality might have significant effects on market dynamics, but the precise consequence for market stability and efficiency is hard to predict.

4.2 Disclosure Requirements, the Release of New Information and Market Efficiency: New Insights from Agent-based Models

4.2.1 Research Problem

The simulation results of Contribution 1 are based on one model setup only. Therefore we ask: Are the results of that study robust? How far are the effects of the publication frequency on market dynamics and stability sensitive to the model setup?

4.2.2 Analytic Approach

Three existing agent-based models are modified to test changes of the publication frequency. As in Contribution 1, a distinction is made between subjective distortion (the difference between the price and the fundamental value in the eyes of investors) and objective distortion (the difference between prices and the true intrinsic value). Other measures are market volatility and the tail index of the return distribution.

4.2.3 Results

Being a very robust result, a rise of the gaps between moments of publication leads to a rise in objective distortion. For the subjective distortion and the volatility of prices, no significant effect can be found. Both results apply for all of the models tested. However, the publication frequency affects the statistical properties of the return distribution. We find longer gaps decrease the tail index, i.e., produce a larger share of extreme returns. Surprisingly, this effect is most pronounced if information are disseminated every quarter of the year – the publication frequency applicable, for instance, to firms listed in the German stock market index DAX. In sum, these results suggest that several effects are quite robust to the model design. This gives evidence to believe that the effects are also valid in real financial markets.

4.3 Fund Managers: Why the Best Might be the Worst – On the Evolutionary Vigor of Risk-Seeking Behavior.

4.3.1 Research Problem

Typically, economic models assume agents either to be risk-averse or risk-neutral. The financial crisis indicates that these assumptions might sometimes be misleading. Hazardous investments proceeding to the meltdown suggest that economic agents did not avoid risks at all but rather sought them. The economist Nassim Nicholas Taleb (Taleb, 1997), a former fund manager, conjectures such behavior to be related to the competition between agents. This motivates the investigation of the competitive advantages of different risk preferences.

4.3.2 Analytic Approach

The first part of the paper is an algebraic analysis which illustrates the potential of the risk-seeking behavior in competitive environments. In the second part, an agent-based model of the professional competition between mutual fund managers is introduced. The goal is to identify the investment behavior which is fittest for variable settings of competitive conditions. To this end, an evolutionary algorithm is used.

4.3.3 Results

The central insight of the algebraic analysis is as follows: Any less capable group can succeed in competition with a higher capable group if it undertakes enough risk and if the outcome needed to survive is sufficiently high. The reason is that risk-seeking behavior per se can provide evolutionary fitness. The agent-based model confirms and extends this finding. Agents tend to build riskier portfolios if competitive pressure increases. If pressure is extreme, not skill is rewarded with evolutionary fitness but risk-taking only. In particular it is shown that, whereas under normal circumstances evolution selects managers with efficient portfolios, here this tendency is offset. These results are alarming as they show that intense competition might not lead to the survival of the best but of lucky risk-seekers. As a result, economic stability is undermined.

4.4 Removing Systematic Patterns in Returns in a Financial Market Model by Artificially Intelligent Traders

4.4.1 Research Problem

As mentioned in Section 2.3, one of the most important stylized facts of financial markets is uncorrelated returns. Typically, agent-based models of financial market replicate this property by implementing noise terms which tend to blur any systematic pattern in the dynamics of prices. For real financial markets, the absence of systematic patterns is sometimes argued to be a matter of logic. Once a systematic pattern is detected, agents would start to exploit it, which would ultimately lead to the removal of the pattern. The present study seeks to imitate this logic and thereby to explain uncorrelated returns based on the behavior of intelligent agents.

4.4.2 Analytic Approach

As a base configuration, a simple agent-based model is developed according to the fundamentalist-chartist approach. Switching between strategies occurs based on the profits they generate. The interplay of fundamentalist and chartists produces fluctuations of prices around the fundamental value – a simple systematic pattern. To illustrate how this pattern can be removed, a group of intelligent agents is induced. The detection of patterns and the prediction of prices is performed by an ANN. Since ANNs are inspired by the human brain, this may be a very natural replication of how systematic patterns are removed in reality.

4.4.3 Results

The simulation experiments show that the intelligent agents are able to exploit systematic patterns and to remove them. An interesting property of the model dynamics is that the fraction of pattern exploiters tends to fluctuate. The reason is that exploiters attain superior profits as long as patterns are present, but this advantage disappears once the patterns are removed. Finally, it is discovered that the influence of pattern exploiters tends to improve market efficiency. Only if the fraction of exploiters is very large, may this effect revert itself.

4.5 High Frequency Trading and its Influence on Market Dynamics: Insights from Agent-Based Modeling

4.5.1 Research Problem

In the last decade, High Frequency (HF) trading – i.e. trading performed by computers with reaction speeds of some microseconds – has spread enormously. Today, a significant part of trading in global financial markets is due to HF-traders. Financial institutions, such as central banks, have great interest in understanding how this fundamental transformation of trading influences financial market dynamics. In this context, I have been engaged by the Bank of England to explore HF-trading by agent-based modeling. Some of the most important research questions of the Bank of England have been: Does HF-trading destabilize financial markets? Is it true that HF-trading improves market liquidity, and is there a difference between normal times and times of stress? Does HF-trading reduce the attractiveness of fundamental analysis? Will market making increasingly congregate around HF-traders?

4.5.2 Analytic Approach

In contrast to other approaches which treat HF-traders as a rather homogenous group, we believe that the effect of HF-trading is sensitive to the particular trading strategy they use. The analytical approach accounts for this. In the base setting only low frequency traders are active. Then, various groups of traders are induced who differ in terms of their speed and their strategy. This allows the distinguishing between the effects of both attributes. Due to the extraordinary requirements of the research problem, the model comes up with three special properties. (i) To account for the low horizon of HF-traders, each simulation run represents one day of trading. (ii) To investigate effects on market liquidity and aspects of infrastructure, trading occurs via a double order book. (iii) To vary the speed of trading with arbitrary precision, the model uses an event-driven approach. The model is fitted to the equity of Lloyds Plc. based on eight indicators of market dynamics and trading.

4.5.3 Results

Surprisingly, the simulations show that the effect of a particular strategy on market dynamics is more pronounced if the strategy is used in low rather than in high frequency. By varying the model setup, we find that the reason is the strong inventory control of HF-traders. Since HF-traders seek to keep their inventory close to zero, they need to reverse any transaction quickly. In this way, they tend to neutralize their influence on the dynamics of prices. The dynamics are destabilized, however, if HF-traders act as market makers. The reason is that HF-traders improve market liquidity and, thus, facilitate technical trading. Further, HF-market makers gain superior profits compared to the respective low-frequency group because they react more quickly in moments when the bid-ask spread – and thus profit opportunities – are great. We find no evidence that HF-trading would undermine the attractiveness of fundamental analysis. In conclusion, these and other results indicate the effect of pure speed for market dynamics to be lower than expected. More important are the strategies applied by investors, the volume due to a particular strategy and the intensity of inventory control.

5. CONCLUDING REMARKS

In the five contributions of the present dissertation, very different, contemporary problems in the domain of financial market research have been tackled: Tests of policy parameters (Contribution 1 and 2), analyses of the behavior of agents under different competitive conditions (Contribution 3), explanations of stylized facts (Contribution 4), and the exploration of different types of trading behavior (Contribution 5). In these studies, the simulation of agent-based models has proven to be a successful tool to gain relevant insights. Nevertheless, the method is not free from specific challenges. Critique of agent-based models sometimes refers to the so-called "many-degrees-of-freedom problem" (see Hommes, 2006, p. 1114, or LeBaron, 2006, pp. 1222). If agents are assumed to follow homo-oeconomicus principles, it is usually quite clear what these principles are (e.g. the maximization of a well-defined utility function). However, if agents are assumed to act behaviorally, the sacrifice of more realism is the loss of a clear guideline stating how agents should be modeled; plainly speaking: There is just one way of acting rationally but many ways of acting irrationally. This problem also affects the model calibration. Often, agent-based models contain a large set of parameters, and turning the screws just slightly may have strong effects on the model behavior.[12] For the addressees of agent-based models, the many-degrees-of-freedom problem underlines the need for careful consideration of the assumption under which results are obtained. The validity of this recommendation, however, might stretch beyond the domain of agent-based modeling.

The many-degrees-of-freedom can be reduced in several ways: (i) by a thorough empirical foundation of the model structure, (ii) by a diligent validation of the model behavior, or (iii) by tests of the robustness of the results obtained. Still, the many-degrees-of-freedom problem extends to these checks themselves. For example, it is the modeler's choice which empirical evidence the model structure should replicate or which indicators should be considered for the validation of the model behavior. Needs for future research may strive to propose objective standards on how these checks are to be done. This endeavor might lead to the optimization of the model quality, to stronger confidence in the model results, and ultimately to a greater influence of agent-based studies in institutional decisions about financial markets.

[12] LeBaron (2006) stresses another aspect that is often neglected: the issue of timing. Dynamic models require the determination of a certain sequence in which all action must take place. According to LeBaron (2006), this sequence is sometimes established in a rather arbitrary manner, though it may be crucial for model behavior.

Despite these issues, an agent-based model can be very valuable, even if the many-degree-of freedom problem is not dissolved perfectly. It is valuable if it illustrates important relations between micro structure and macro behavior which have not been known ex ante. This potential of agent-based modeling might be its greatest benefit, and this benefit may help, in particular, to achieve a better understanding of financial markets.

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B

Contributions

1

Temporal information gaps and market efficiency: a dynamic behavioral analysis

Björn-Christopher Witte

Abstract: This study seeks to explore, how market efficiency changes, if ordinary traders receive fundamental news more or less often. We show that longer temporal information gaps lead to fewer but larger shocks and a reduction of the average noise level on the dynamics. The consequences of these effects for market efficiency are ambiguous. Longer temporal information gaps can deteriorate or improve market efficiency. The concrete result depends on the stability of the market together with the interval in which the length of the gap is incremented.

Keywords: Temporal information gaps, market efficiency, disclosure policy, agent-based financial market models, technical and fundamental analysis.

JEL classification: G12; G14.

1. INTRODUCTION

Conceived in the 1960s the Efficient Market Hypothesis (EMH) has become one of the most famous economic paradigms. It states that security prices fully reflect all available fundamental information. Fama (1970) has differentiated three interpretations of such efficiency. The following formulation rests partly on Jensen (1978):

In general a market is efficient with respect to information set θ_t if θ_t is properly reflected in prices.

- In the weak form, θ_t comprises solely the information contained in the past price history of the market as of time *t*.
- In the semistrong form, θ_t comprises all information publicly available at time *t*.
- In the strong form θ_t comprises all information known to anyone at time *t*.

In the past thirty years lots of empirical (e.g. Shiller 1981, Cutler et al. 1989, Lev 1989, Mitchel and Mulherin 1994) as well as some analytical findings (Grossmann and Stieglitz 1980, Shleifer and Vishny 1997) have challenged the EMH. The flourishing field of behavioral finance (see, e.g. Shleifer 2000, Hirshleifer 2001, Shiller 2003, or Lo 2004) has proposed some explanations of its failing. The central insight is that agents do not process information fully rationally but follow sentiments and commit systematic errors. Still, this view simplifies the reality of financial markets. Due to publicity laws and corporate disclosure policies, for instance, traders do not even receive fundamental information currently. Our analysis focuses on this fact and its consequences for market efficiency.

The underlying question of our research is: How does market efficiency change, if ordinary traders receive fundamental information more or less often? In this context, the term ‘Temporal Information Gap’ (TIG) will denote the span of time in which traders do not receive any fundamental news. For the purpose of a deeper classification of the research problem, let us conceptualize the process of value discovery as a complex process. The computation of the proper fundamental value necessitates three conditions:

(1) Fundamental data must be available. In reality, disclosure regulations make it obligatory for firms to disseminate fundamental data only at discrete steps of time.

(2) Fundamental data must be complete, correct and definite. In reality, disclosure regulations do not prescribe to publish all value-relevant information and give considerable leeway to creative accounting.

(3) Agents must know the exact relationship between fundamental information and value. Not every real trader is an expert and uses rational methods to compute the true value out of the bulk of data. Additionally, the methods themselves are diverse and approximative.[13]

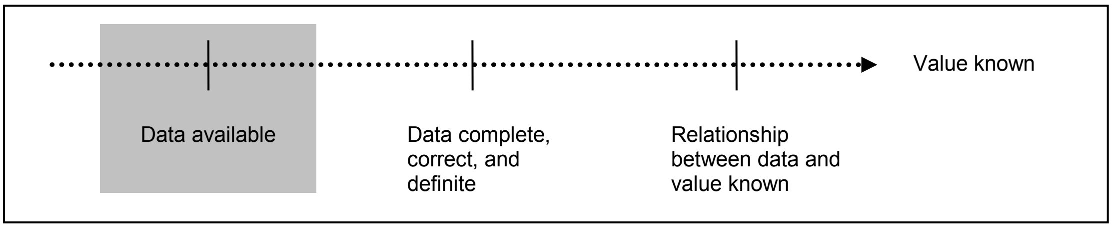

Figure 1: Discovery of fundamental value as a complex process

Figure 1 illustrates the process of value discovery. The process implicates the possibility of information gaps on the side of traders. The term 'information gap' originated in agency theory, where it is used synonymously for the deficit of information of the agent relative to the principal. Regarding the process of value discovery, two causes of such an information deficit become apparent. First, agents have not received the latest information and second, agents have received the latest information, but the information lacks content. Accordingly, we denominate the first form of information gap as 'temporal' and the second as 'substantive'. Temporal as well as substantive information gaps can arise in various extents. The extent of a TIG is determined by the time that agents lack current information. We specify the TIG as the number of periods in which agents do not get any news. At the end of a TIG, e.g. via corporate disclosure, agents receive all information. We assume that once the information is public, the true fundamental value is known to traders, that is, conditions (2) and (3) are fulfilled.[14]

To conduct our analyses, we construct an agentbased model of a financial security market. The Chartist-Fundamentalist Approach (CFA) has proven to be a powerful tool in this area (for recent surveys, see Hommes, 2006; LeBaron, 2006; Westerhoff, 2008, 2009). The behavioural approach is based on the observation that financial traders use two main strategies: fundamental and technical analyses. Fundamentalists fix their orders to economic fundamentals, whereas chartists try to predict prices by simple technical trading rules based

[13] For an overview of common methods see Brealey et al. (2006).

[14] One may wonder why we do not simply speak of information lags instead of TIGs. The reason is that the term 'information lag' suggests that all information is disclosed with the same delay. This does not apply to our model since we assume information of different periods to be released in a bundle.

upon patterns in past prices, such as trends. The interplay of both strategies creates model dynamics that replicate some stylized facts of real financial markets.

What might be a reasonable assumption about the relationship of TIGs and market efficiency? Consider that the forces of arbitrage tend to adjust prices to the value which arbitrageurs assume to be proper. TIGs make possible that this estimation is already misaligned in reference to the true fundamental value. Clearly, the misalignment tends to be heavier, the less often arbitrageurs receive fundamental information, i.e. the longer the TIG. One may conclude that longer TIGs should lead to a fall of market efficiency, at least in the strong form. Market efficiency in the semistrong form might not be influenced by TIGs, since the concept merely measures the difference between true prices and arbitrageurs' subjective fundamental perception while ignoring the objective misalignment of the latter.

The results of our study run counter to these intuitions. Longer TIGs do not always mean a fall of market efficiency. The explanation lies in the complex effects of TIGs on price volatility. We observe that, under certain circumstances, longer TIGs tranquilize market dynamics, which in turn improves efficiency. Thus, even if longer TIGs increase the bias between the true fundamental value and the perception of traders, market efficiency, in each form, improves if the volatility effect is strong enough. The analysis will show that the overall effect of larger TIGs on market efficiency depends on the endogenous stability of the market and on the interval in which the TIG is incremented.

This article is organized as follows: Section 2 is dedicated to a deeper theoretical foundation of our project. We recapitulate the state of efficiency research and conceptualize the process of value discovery. Section 3 derives the relationships between TIGs and the noise affecting the market. In Section 4 we introduce the CFA and develop a dynamic behavioral model accordingly. It presents the model simulations, resumes the complex results and intends to provide interpretations. Section 5 underscores the relevance of the results in the context of corporate disclosure policy and institutional regulation. Finally, in Section 6, we summarize the most important findings.

2. TEMPORAL INFORMATION GAPS AND NOISE

This Section is dedicated to TIGs, noise and the relationship between both. Economics refer to noise in many contexts and use the term with different connotations.[15] In the context of our

[15] Black (1986) provides an overview of different fields and senses in which noise affects market efficiency.

study we define noise as an exogenously driven influence on the dynamics of prices. Shocks are understood as singular occurrences of noise.

In general, exogenous influences on the dynamics of prices arise from changes of the fundamental data. If fundamentals change, traders will compute a new fundamental value, reformulate their orders respectively and prices will adjust to the new demand. Clearly, this mechanism requires that traders are informed about the occurrence which has shifted fundamentals. As long as fundamental movements are not communicated to traders, they will not manipulate the dynamics of prices. During the TIG, therefore, no shocks will appear. This observation enables us to specify the initial definition of shocks: shocks consist in the recognition of fundamental changes from one observation step to another. Let the parameter gap denote the length of a TIG. It follows that a shock will arise every gap-th period. Formally,

$$t_{shock} = n * gap; \qquad n = 1,2,\ldots N, \tag{1}$$

where t_{shock} denotes any period in which a shock affects the dynamics of prices.

What can be said about the relationship between *gap* and the average 'size' of the shocks? If the true fundamental price follows a random walk, it will tend to drift apart from an initial value over time. Accordingly, as long as traders are not informed about fundamental movements, the deviance between their subjective pricing of the fundamental value and its true level tends to rise. Thus, when traders finally learn the relevant data, the perceived change of the fundamental value will on average be the heavier, the longer the preceding TIG has been. We conclude that the shocks on the price dynamics will be the stronger, the higher the TIG.

The exact quantitative relationship is easy to derive. Assume that the evolution of the fundamental value (F) is defined by

$$F_{t+1} = F_t + R_t; \qquad R_t \sim N(0, \sigma^2), \tag{2}$$

where R_t is the change of fundamentals in period *t*. R_t is a normally distributed, independent variable with mean 0 and variance σ^2. The normal distribution holds that if X and Y are independent normal random variables with $X \sim N(\mu_X, {\sigma_X}^2)$ and $Y \sim N(\mu_Y, {\sigma_Y}^2)$, then their sum U is normally distributed with $U = X + Y \sim \mathrm{N}(\mu_X + \mu_Y, {\sigma_X}^2 + {\sigma_Y}^2)$.

It follows that if $R_1, R_2, \ldots, R_n$ are independent normal random variables with $R_1 \sim N(0, \sigma^2)$, $R_2 \sim N(0, \sigma^2)$, …, and $R_n \sim N(0, \sigma^2)$, then their sum S is normally distributed with $S = \sum_i^n R_i \sim \mathrm{N}(0, n\sigma^2)$.

This means that if traders learn the fundamental value every gap^{th} period, the variance of the perceived value changes, and therefore the size of the shocks will be gap-times the variance of the periodical change of fundamentals. Formally:

$$\sigma_{shock}{}^2 = gap * \sigma^2, \tag{3}$$

where $\sigma_{shock}{}^2$ is the variance of shocks. Since the mean noise equals zero, the variance σ^2 is computed by

$$\sigma^2 = E[R^2], \tag{4}$$

where $E[R^2]$ is the expected value of the squared fundamental changes. From Equations 3 and 4 for we thus derive:

$$\sigma_{shock}{}^2 = gap * E[R^2], \tag{5}$$

Let R_{shock} denote the occurrences of shocks, then due to Equation 5 the following relationship must be valid:

$$\sigma_{shock}{}^2 = E[R_{shock}{}^2], \qquad \text{with } R_{shock} = \sqrt{gap} * R. \tag{6}$$

From 6 we have:

$$\phi R_{shock} = \sqrt{gap} * \phi R, \tag{7}$$

where ϕR_{shock} is the average absolute shock and ϕR the average absolute periodical change of fundamentals. Accordingly, the average size of the shock after gap periods of zero fundamental news received by the traders will be $\sqrt{gap}$-times the average periodical change of fundamentals.

In summary, we could detect two effects of TIGs on noise:

(A) The higher the TIG, the less often shocks hit the dynamics of prices.
(B) The higher the TIG, the heavier the shocks will be.

As exogenous shocks are generally known to destabilize dynamics, the two effects must rival each other. When TIGs grow, the effect of fewer shocks (A) tends to stabilize the dynamics, whereas the effect of heavier shocks (B) is destabilizing.

Which of the two effects prevails with respect to the average noise level? We define the average noise level as the mean shock averaged over all transaction periods, no matter if a shock appears or not. Formally:

$$\phi R_{noise} = \phi R_{shock} / gap. \tag{8}$$

Clearly, if traders correctly perceive fundamentals in every period, all fundamental movements will be transferred into reactions of demand and prices somehow. This is different if traders learn the true fundamentals every gap^{th} period, with gap > 1. Probably, if gap is high, not all fundamental changes in the span of gap periods push fundamentals in the same direction. When traders finally learn the true fundamental value, movements will have offset each other to some degree. The sum of changes which are actually transferred into formulations of demand and prices will be lower than the sum of changes in total. The extent to which fundamental occurrences compensate each other tends to rise, the less often the relevant information is available, and fewer changes will be transferred into shocks. Therefore, the average noise level declines when incrementing the TIG. Note that the compensation-effect is also the cause, why by Equation 7 a higher TIG raises the mean size of the shocks only under proportionally.

From Equations 7 and 8 the exact relationship between gap and the average noise level can be deduced as:

$$\phi R_{noise} = \frac{1}{\sqrt{gap}} * \emptyset R, \qquad (9)$$

Let us summarize our findings in a pragmatic form:

Every quadruplication of the TIG will…

- …quarter the number of shocks in a finite span of time by Equation 1.
- …double the mean size of the shock by Equation 7.
- …halve the average noise level by Equation 9.

We conclude that the consequences of TIGs for price dynamics are ambiguous. TIGs lead to fewer shocks but enlarge them. The result that the average noise level is reduced suggests that TIGs might stabilize market dynamics. However, the further analysis will show that this idea is sometimes wrong.

3. THE MODEL

3.1 Motivation

The notion of price adjustment and value discovery as complex processes call for a dynamic analysis. The psychological aspects of value discovery implicate a behavioural view. Drawn together the project demands a dynamic behavioural approach. The CFA matches these needs. The CFA is a specification of agent-based modelling approach, targeting the exploration of financial market dynamics.

Models with heterogeneous agents have proven to be quite successful in the past and have sharpened our understanding of the dynamics of real financial markets. Agent-based modelling rests on the wellsupported evidence that individuals are boundedly rational (Simon, 1955; Kahneman et al., 1986; Smith 1991). In order to find orientation and to compensate their lack of knowledge, agents rely on heuristics, that is, behavioural rules. This is also true for agents in financial markets. A broad stock of empirical evidence agrees that investors apply either fundamental or technical trading rules (e.g. Taylor and Allen, 1992; Menkhoff, 1997; Lui and Mole, 1998). The CFA reproduces the generic ideas of the two strategies: fundamentalists trade on fundamental information. They evaluate economic, industrial and corporate conditions in order to estimate the value of an asset as the present value of the expected future dividends. Fundamentalists expect prices to return to value sooner or later. Consequentially, they try to exploit mispricing. The strategy aims at long-run profits (Graham and Dodd, 1951; Greenwald et al., 2001). In contrast, chartists trade with the trend. They regard past price movements as an indicator of the market sentiment. Consequentially, chartists extrapolate price trends. The strategy aims at shortrun returns (Edwards and Magee, 1966; Pring, 1991; Murphy, 1999).

CFA-models displaying the interaction of both agent groups can create complex nonlinear dynamics. Some of these models replicate the stylized facts of real financial markets quite adequately. Among those facts are: bubbles and crashes, excessive volatility (variations of prices that cannot be justified by fundamental news), non-normal distributed returns, and volatility clustering (alternation of periods of low and high volatility).[16]

With reference to the market dynamics, each group of investors plays a different role. The effect of fundamentalism is comparable with arbitrage. The strategy leads to a reduction of the mispricing adding a negative feedback to the dynamics. The extrapolation of price trends by chartist brings a positive feedback and produces market inefficiency.

The model-driven CFA affords several methodical advantages. The method enables to precisely gauge all variables, control for exogenous shocks and generate as much data as needed.

3.2 Setup

The model we use here may be regarded as an extension of the model developed in Westerhoff (2003a). The ‘setup’ can be summarized as follows: we look at a stylized

[16] For a deeper study of stylized facts see Mantenga and Stanley (2000), Cont (2001), Lux and Ausloos (2002), Johnson, Jefferies and Hui (2003) or Sornette (2003).

speculative market of financial securities. Traders can switch between technical and fundamental strategy. For every period, the fraction of traders relying on each trading rule depends on the current distortion of the market. For every gap period, agents update their cognition of the fundamental value. After having chosen a strategy, agents formulate their orders accordingly. The resulting excess demand generates the price of the next
period at last.

In our model we differentiate two conceptualizations of the fundamental value: the objective and the subjective one. The objective fundamental value refers to the price omniscient, and perfectly rational agents would compute as the proper security price. In this sense the objective fundamental value equals the true fundamental value. We assume insiders to have such a view. Contrarily, the subjective fundamental value corresponds to the imperfect perception of traders who are affected by TIGs.

In order to model the objective fundamental value, we keep up the general assumption for the evolution of fundamentals made in Equation 2. Let F^O denote the objective fundamental value, then

$$F_{t+1}^{O} = F_t^{O} + R_t; \qquad\qquad R_t \sim N(0, \sigma^2), \tag{10}$$

R_t still denotes the change of fundamentals in period t, since every new fundamental occurrence will instantly effectuate an adequate adjustment of the objective fundamental value.

In order to model the subjective fundamental value, we assume that ordinary traders correctly compute the true fundamental value once they learn all relevant information. Contrarily, when no news reaches investors, they will base their calculations on the most recent data. Note that traders receive fundamentals every *gap^th* period. We formalize

$$F_{t+1}^{S} = \begin{cases} F_{t+1}^{0}, & t+1 \in \{gap, 2gap, \dots, Ngap\} \\ F_t^{S}, & otherwise \end{cases} \tag{11}$$

Equation 11 states that the subjective fundamental value equals the objective fundamental value every *gap^th* period, as traders catch up their information deficit at all these steps. In all other periods the subjective fundamental value of tomorrow remains the same as today, since traders reckon the same old numbers.

Let us turn to the inner working of the market. The price adjustment process is given by a so-called price impact function (Farmer and Joshi, 2002). A price impact function relates today’s excess demand for an asset to the change of the price from today to tomorrow. The excess demand equals the sum of the individual demands of chartists and fundamentalists weighted with their relative fraction in the market. Accordingly, the security price S in period *t+1* is given by

$$S_{t+1} = S_t + a^M(W_t D_t^C + (1 - W_t) D_t^F), \tag{12}$$

where D_t^C and D_t^F stand for the demand of chartists and fundamentalist respectively, and W_t denotes the relative fraction of chartists. a^M is a positive price adjustment coefficient. According to Equation 12, excess buying drives prices up, whereas excess selling drives prices down. The higher a^M, the stronger the reaction of prices will be. The equation is a simplification of the actual order matching mechanism. It may be interpreted as a stylized description of the behavior of risk-neutral market makers who adjust prices with respect to excess demand.

The demand of chartist can be written as

$$D_t^C = a^C(S_t - S_{t-1}), \tag{13}$$

with the positive parameter a^C regulating the aggressiveness of chartists. Chartists bet on the latest price trend to go on. Hence, they receive a buying (selling) signal if the current price exceeds (undercuts) the price level one period before.

The orders generated by the fundamental strategy can be expressed as

$$D_t^F = a^F(F_t^S - S_t), \tag{14}$$

where a^F calibrates the strategy's aggressiveness. Fundamentalists believe that prices tend to revert to the fundamental value. Therefore, they get a buying (selling) signal if prices are above (below) the fundamental value. Since traders do not always know the true fundamental value, the subjective fundamental value is relevant here.

Finally we formalize the weight of chartist as:

$$W_t = \frac{1}{1 + b^1 + b^2 (F_t^S - S_t)^2} \tag{15}$$

The equation represents the switching mechanism of traders between technical and fundamental strategies. The more the prices deviate from the value, the more the traders adhere to the fundamental analysis. The arguments of Black (1986) and Hommes (2001) support the intuition. According to Black, trading on information (i.e. fundamentalism) instead of noise (i.e. chartism) promises more profits to exploit, the higher the distortion of prices. Hommes argues that if prices deviate strongly from the fundamental value, a consolidation is probable. Fundamental trading rules prescribing to trade against the bubble become attractive. In contrast, technical strategies which rely on the bubble's growing inflation become risky.

b^1 and b^2 (Equation 15) are positive parameters regulating the quantitative dimension of the bell-shaped function. The higher the b^1, the greater the proportion of traders who never desist from fundamental trading. The higher the b^2 the faster the traders switch to fundamentalism when prices disconnect from fundamentals. Again, the perceived subjective fundamental value is important here.

3.3 Calibration

Taylor and Allen (1992) report that 5–10% of traders always stick to fundamental analysis. b^1 = 0.1 is consistent with this finding. b^2 is set to 100. We choose a^M = 1 and a^F = 2. The reaction-coefficient left to configure is a^C. Westerhoff (2003b) indicates that the interaction of traders might reproduce some of the stylized facts of financial markets purely endogenously. Accordingly, we choose a^C such that the model yields complex dynamics even with constant fundamentals (σ = 0). This applies for a^C in the range of 2– 8. In the following simulations we will vary a^C within these restrictions in order to carry out the analysis under different market conditions. Depending on the simulation run we will set σ to 0 or 0.2.

4. SIMULATIONS

4.1 Capturing Efficiency

The model we have built allows testing for all three forms of market efficiency. We concentrate on the semistrong and the strong form. We measure market efficiency in terms of volatility and distortion. We define volatility as the average of absolute returns, that is,

$$ØV = \frac{1}{n}\sum_{t=1}^{n}|S_t - S_{t-1}| \quad (16)$$

Relative to volatility, distortion captures market efficiency more directly. We define distortion as the average absolute deviation of prices from its fundamental value. Since our analysis distinguishes objective and subjective fundamentals, we come to two versions of distortion. The first version is

$$ØD^O = \frac{1}{n}\sum_{t=1}^{n}|S_t - F_t^O| \quad (17)$$

The formalization gives the average absolute deviation of prices from objective fundamentals. As the objective fundamental value represents the insider view, the equation directly yields a measure of market efficiency in the strong from. The second version is

$$ØD^S = \frac{1}{n}\sum_{t=1}^{n}|S_t - F_t^S| \quad (18)$$

The formalization gives the average absolute deviation of prices from subjective fundamentals. Since the subjective value accounts for the information publicly available, the equation directly yields a measure of efficiency in the semistrong form.

4.2 Some Numerical Results

The tools just developed enable us to evaluate the simulation runs presented in this section. For every run, a legend on the right displays the measures of volatility ($\emptyset V$) as well as subjective ($\emptyset D^S$) and objective distortion ($\emptyset D^O$).

We first want to get a feeling for the endogenous dynamics of the model. By setting τ to zero F^O remains constant to 100 over time. Accordingly, no noise will disturb the dynamics. Figure 2 shows the evolution of prices for two different values of a^C. In the first run a^C equals 2, in the second a^C has been altered to 8. Remember that a^C represents the reaction intensity of chartists.

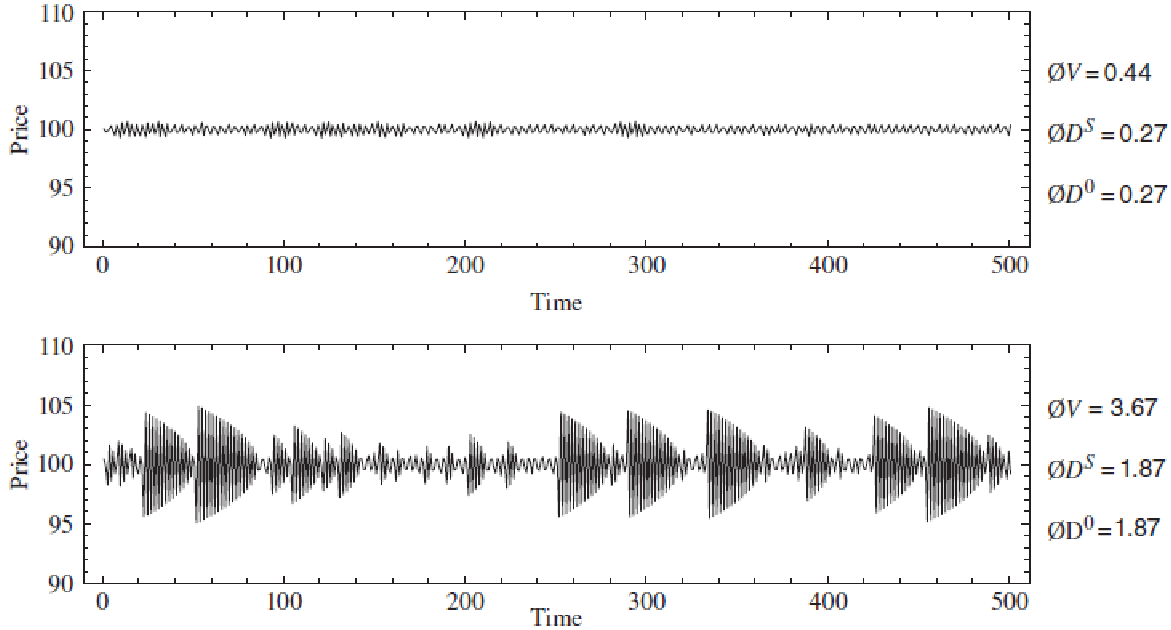

Figure 2: The panels show the dynamics of prices for different values of a^C, the reaction parameter of chartists. In the first panel a^C = 2, in the second a^C = 8. Volatility (ØV) and distortions (ØD^o, ØD^s) of the respective simulation run are appended on the right. No noise was added.

Watch the upper simulation run first. The dynamic of prices follows a rather complex walk neither reaching an equilibrium state nor a regular attractor. Considering the absence of fundamental news, the volatility of 0.44 must be completely excessive.

Furthermore, the dynamics switches between intervals of calm (e.g. from t = 225 to t = 275) and turbulent (e.g. from t = 80 to t = 160) motion. This phenomenon is known as on-off intermittency. On-off intermittency is a form of volatility clustering which is produced completely endogenously. For the objective fundamental value being constant over time, there is no TIG in the cognition of traders. The subjective and the objective fundamental value coincide. As a result, objective and subjective distortion are equal ($\emptyset D^S$ = $\emptyset D^O$ = 0.27). In general, our model replicates some of the stylized facts of real financial markets.

Now contemplate the run below. Remember that the chartist strategy is calibrated to be more aggressive. We observe that the volatility of the dynamics has risen remarkably. This is true for intervals of low and high volatility. Furthermore, on-off intermittency has become distinctive. From time to time and without apparent reason the dynamic jumps into a phase of extreme fluctuations. In the following, the oscillations decline gradually and finally settle down to the normal level. Overall, the average volatility has climbed to 3.67. Moreover, the higher volatility has caused an increase in distortion. Subjective and objective distortions have reached at 1.87. In general, the higher intensity of chartism has deteriorated market efficiency considerably. The observation holds for efficiency in its strong and in its semistrong form.

For the following analyses we set σ to 0.2. The objective fundamental value now moves in every transaction period. This is a necessary condition for the study of TIGs. For TIGs greater than one period, ordinary traders will have an information deficit relative to insiders. Figure 3 resumes the results for a^C = 2. The length of the TIG has been varied. The first three panels show exemplary simulation runs for different gaps. For every run the curve of prices together with the curve of objective fundamentals are drawn. The two panels on the bottom aggregate the results of several simulations.

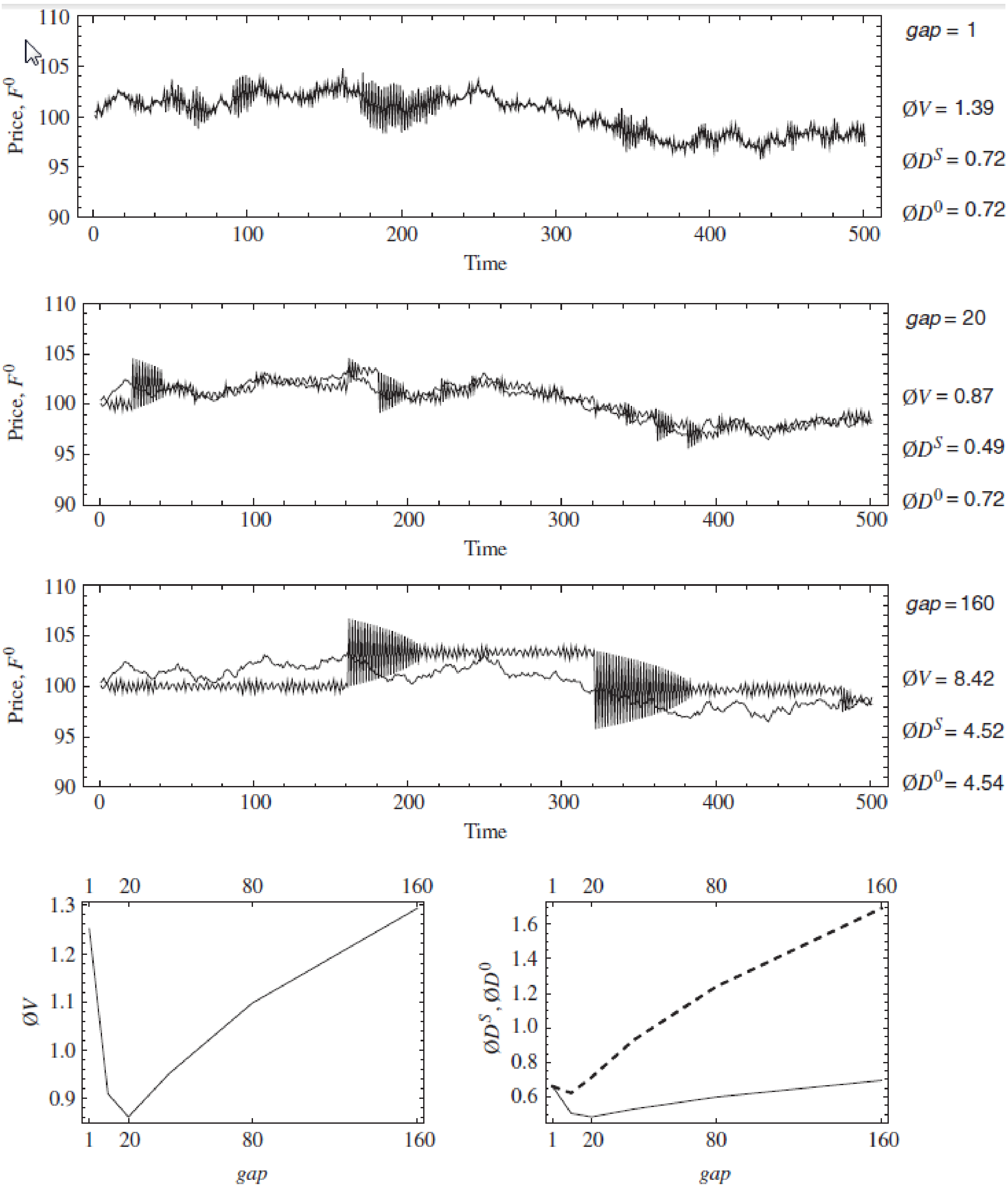

Figure 3: The first three panels show the evolution of objective fundamentals (thin line) and the dynamics of prices for different information-gaps. In the first panel the dynamics of prices covers the evolution of fundamentals visually. The measure of volatility (ØV), subjective distortion ($\emptyset D^{s}$), and objective distortion ($\emptyset D^{o}$) for the respective simulation run are appended on the right. The random walk of objective fundamentals is the same for all three simulations. The left panel below illustrates volatility, the right panel subjective and objective distortion (dashed line), depending on the gap. Volatility and distortions were measured for gaps of 1, 10, 20, 40, 80 and 160; results are based on twenty simulation runs of 5000 periods each for every gap. Parameter $a^{C} = 2$. For other parameters see Section "calibration".

In the first simulation run *gap* equals one period. Accordingly there is no TIG. The subjective value equals the objective one. Objective and subjective distortion correspond. Since the fundamentals now follow a random walk, the level of prices changes over time.[17] Moreover, intervals in which prices strongly fluctuate around the subjective value (e.g. from t = 170 to t = 230) alternate with periods in which prices follow value rather accurately (e.g. from t = 230 to t = 330). Relative to the respective simulation run with no noise (Figure 1, first panel), volatility and distortions have risen significantly.

What part of the volatility can be attributed to shifts of fundamentals? In our model σ = 0.2 is equivalent to an average periodical change of the objective value of about 0.16. With a value of 1.39 the measured price volatility is excessively higher. We conclude that the vast majority of price volatility points to true market inefficiency. The measures of distortion confirm the fall of efficiency. Objective and subjective distortion have climbed to 0.72. Evidently, efficiency has deteriorated due to the presence of noise.

In the second simulation run *gap* has been increased to twenty periods. Recall that the demand of traders is based on subjective fundamentals. However, the longer the TIGs, the more the objective value, following a random walk, tends to drift apart from the subjective one. Hence, trading is geared to a level which continuously less corresponds to the true fundamental value. As a result, we expect objective distortion to rise.

Indeed, prices start to disconnect from objective fundamentals. Furthermore, we observe that when traders get to know the latest information, theirm subsequent reaction sometimes entails phases in which volatility is relatively high (e.g. at t = 180). Overall, the average volatility has dropped to 0.87. As a result, the subjective distortion has also declined to 0.49. Moreover, the objective distortion has remained constant at 0.72. This observation strongly contradicts our intuition just established. The solution is that we have ignored the effect of volatility on distortion. Even if prices fluctuate around a less adequate value, the objective distortion has not risen due to the lower oscillations.

In the third run *gap* has been increased another time to 160. The disconnection of prices from objective fundamentals has become unmistakable and more durable than before. When traders get the latest information, their reaction can be drastic. The consequent trading on the news pushes the dynamics into quite long lasting phases in which volatility is pronounced. Apparently, news is not instantly transformed into a new level of prices but initiate a complex adjustment process. Within the phase of adjustment the trading volume is high since agents interact intensively. Fundamentalists directly react to the fundamental news and induce a price trend towards the new fundamental value. Unfortunately, chartists trade on this trend and provoke an overshoot. When the misalignment is too heavy, chartism

[17] We cannot see the curve of objective fundamentals because it is covered by the evolution of prices.

withdraws and fundamentalism takes control again. The mechanism repeats until prices have settled down to their normal attractor. However, the true fundamental value has considerably shifted in the meantime. The dynamics is swinging into a level that does not represent the true fundamental value anymore. Obviously, the adjustment process is too slow to guarantee market efficiency, neither in the strong nor in the semistrong form. On the contrary, arbitrage itself has yield inefficiency by stimulating intense trading volumes and excessive volatility. The efficiency measures reflect the observations. As a result of the turbulent phases, the overall volatility has escalated to 1.55. Because of the higher volatility the subjective distortion has increased to 0.81. Due to the rise of volatility and due to the higher divergence between subjective and objective fundamentals the objective distortion has climbed to 2.02.

The two panels at the bottom confirm the results for a large number of observations. Watch the left bottom panel first. The panel shows the relationship between different TIGs and volatility. We measured volatility for gaps of 1, 10, 20, 40, 80 and 160 periods. For every gap we performed 20 runs of 5000 periods and computed the average volatility. The high number of observations should guarantee that the results are not disturbed by chance. The curve reveals a decline of volatility at the beginning. However, for gaps greater than 20 the volatility increases continuously.

The panel on the right captures the respective measures of objective (dashed curve) and subjective distortion. For small gaps both curves fall indicating lower distortion. For higher gaps the graphs slope upwards, objective and subjective distortion rise. Note that the subjective distortion is solely affected by price volatility. Thus, both curves are alike. Apart from volatility, the rising inadequacy of the subjective value consequent to higher TIGs shapes the curve of objective distortion. As a result, for every gap the objective distortion lies above the subjective one.

We now turn to the case of aggressive chartists setting a^C to 8. Figure 4 illustrates the results. The organization of the panels and the underlying methods of computation are the same as before. Since the dynamics of prices would cover the curve of fundamentals completely, we let the latter apart.

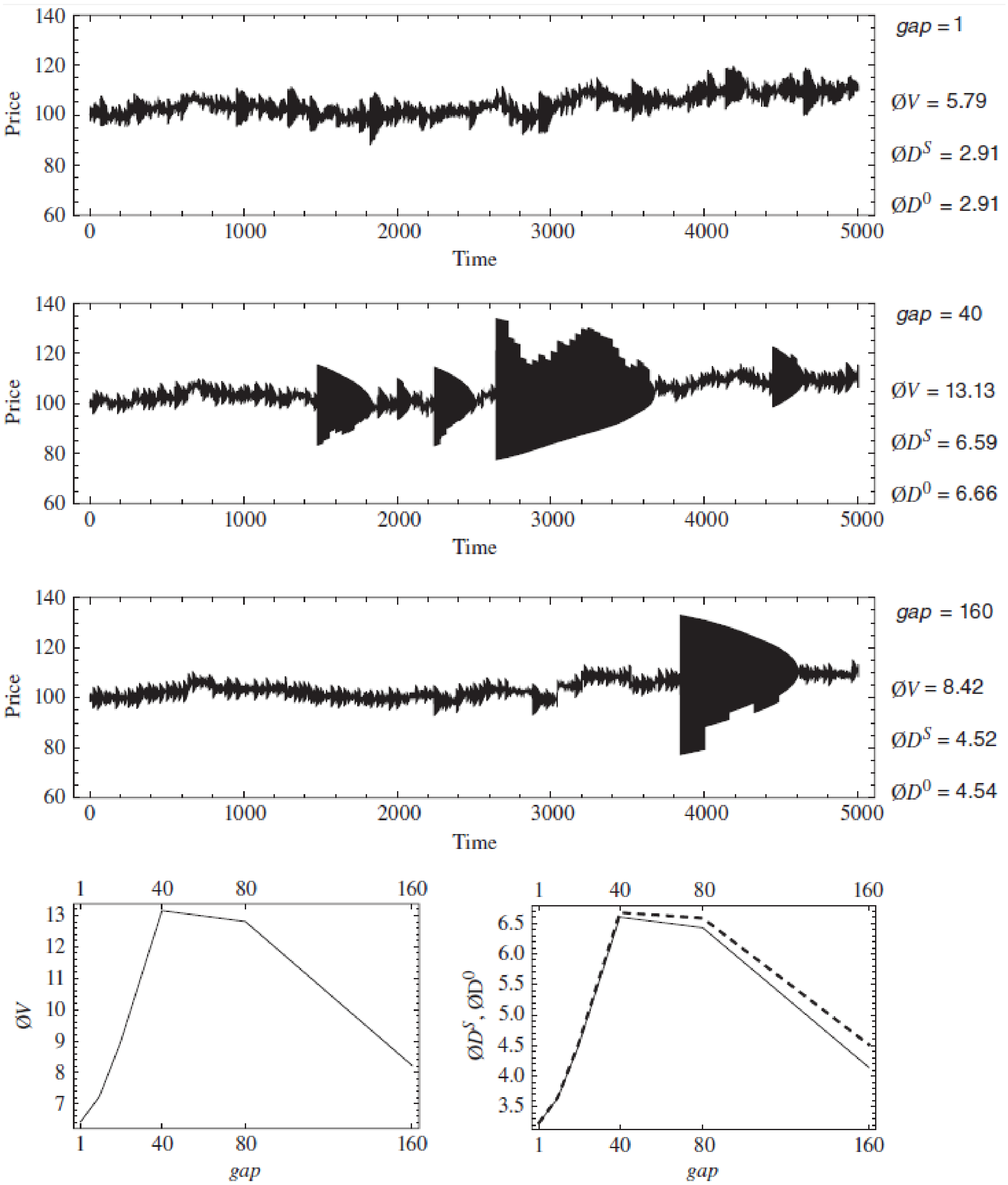

Figure 4: Same as in figure 3, except simulation run panels display prices only. Now parameter $a^C = 8$. For other parameters see Section "calibration".

Let us inspect the topmost simulation run first. Relative to the runs before the measures of volatilities and, therefore, distortions have exploded. Additionally, the effects of higher TIGs have changed. Altering the gap from 1 to 40 has boosted volatility and distortions. Obviously, this is because the dynamics tend to jump into phases of exceeding volatility when traders receive the latest fundamentals after a while of no news at all. However, when we increase the gap further to 160, volatility and distortions decline. The cause is that the number of phases of immense volatility has dropped.

The panels on the bottom mirror the observations. For small gaps volatility and distortions grow, whereas for larger gaps they shrink.[18] Since for all gaps volatility is high in comparison to the change of fundamentals, the volatility effect on objective distortion is highly dominant. As a consequence the curves of subjective and objective are both shaped by volatility leading to similar evolutions of all three graphs.

In comparison with the case of a^C = 2 the curves of volatility and distortions have reverted. Apparently, the endogenous stability of the market, determined by the aggressiveness of chartists, dictates the relationship between TIGs and market efficiency.

Figure 5 merges the results. We have measured volatility, subjective, and objective distortion for different combination of TIGs and parameter a^C. The panels reveal smooth transitions from the level curves for a a^C = 2 (front side) to the level curves of a^C = 8 (back side). The regularity of the relationships can be confirmed.

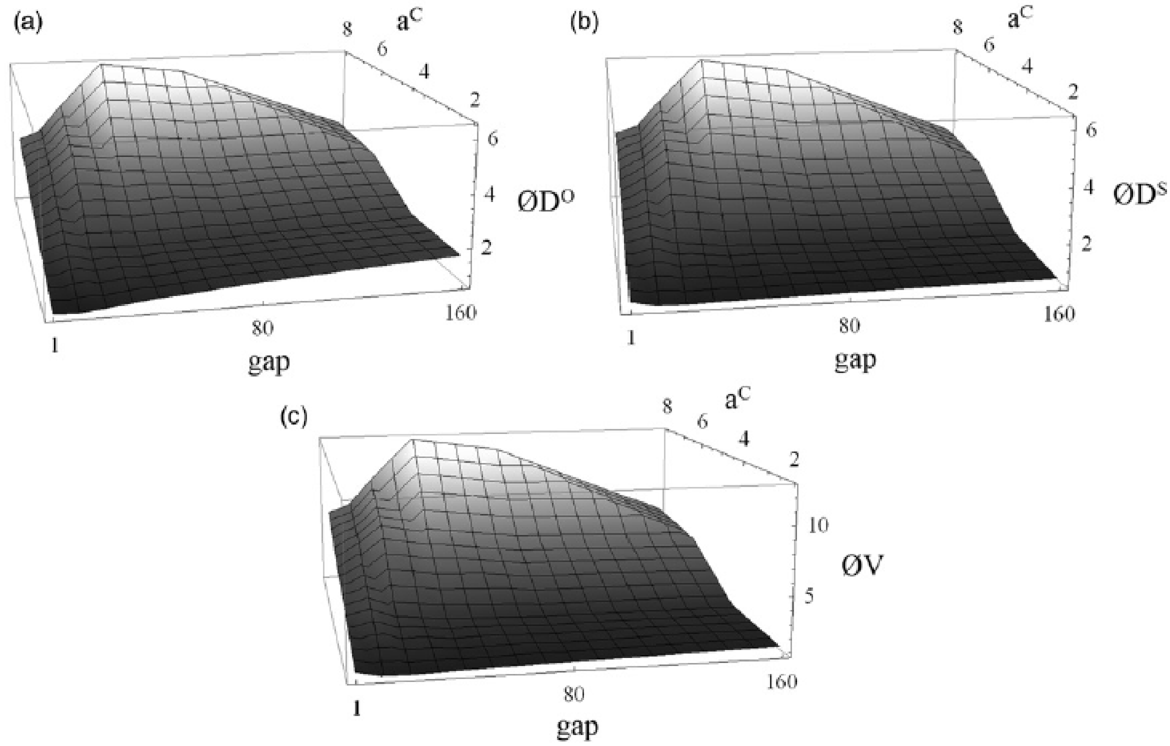

Figure 5: Volatility (left) and subjective distortion (middle) and objective distortion (right) for different combinations of gap and parameter a^C. a^C was set to 2, 4, 6, and 8. Chosen gap lengths were 1, 10, 20, 40, 80 and 160. Average volatility and distortions of every combination are based on twenty simulation runs of 5000 periods.

[18] Clearly, with respect to objective distortion this cannot be the end of the story. If traders would not achieve any information about the true fundamentals (i.e. the gap tends infinity), prices would not follow objective fundamentals at all; objective distortion is maximal.

4.3 Interpretation

What are the reasons for the different relationships between market efficiency and the length of the TIG? The answer lies in the effects of TIGs on the noise impacting the dynamics. As demonstrated in Section 2, longer gaps lead to fewer shocks (A), but heavier shocks (B). The positive consequences of effect A are rather linear; the less often shocks disturb the dynamic, the more often the dynamics follows its natural run. In contrast, the negative consequences of effect B depend on the endogenous characteristics of the market.

If the market is endogenously quite stable ($a^C = 2$), it can compensate a certain size of shocks relatively well. As a result, for small gaps the positive effect A dominates effect B; the average volatility declines. However, if the gap is extensive, the market cannot withstand the shocks anymore and phases of strong volatility appear. Effect (B) dominates effect (A); the average volatility rises.

In the instable configuration ($a^C = 8$) the market is very sensitive to noise because chartists aggressively extrapolate the adjustment reaction of fundamentalists subsequent to news. Hence, even small shocks can trigger phases of huge volatility. As a result, the negative consequences of effect (B) are remarkable from short gaps on; average volatility rises. Nonetheless, incrementing the gap beyond a certain level does not produce additional volatility. The cause is that once the shocks are continuously heavy enough to initiate high volatility phases, effect (A) starts to prevail: shocks become fewer and, thus, fewer phases of high volatility show up; the overall volatility declines.

Market efficiency in the semistrong form, that is, subjective distortion results directly from market volatility. Hence, longer gaps can deteriorate or improve semistrong market efficiency. Market efficiency in the strong form, that is, objective distortion results from volatility and from the bias between subjective and objective value. The bias between perceived and true value tends to rise with larger gaps. Accordingly, we expect strong efficiency to fall. However, if longer gaps simultaneously stabilize the dynamics, the change in volatility sometimes offsets the intuitive relation. We observe this phenomenon especially when the market is endogenously highly unstable ($a^C = 8$). Hence, under certain circumstances longer TIGs improve market efficiency, even in the strong form.

We conclude that the impact of TIGs on market efficiency is ambiguous. Both, strong and semistrong efficiency can rise or fall with larger TIGs. The exact result depends, first, on the endogenous characteristics of the market and, second, on the interval in which we increment the gap.

The observations may be interesting but still do not satisfy. Are the effects of temporary information gaps on market efficiency indeed so intricate? In our model the complexity of the findings is due to the ability of the model to produce turbulent phases in response to shocks of a certain size. The occurrence of phases of abnormal volatility consequent to singular exogenous shocks is denoted as transient behaviour. Is transient behaviour a property of real financial markets? Indeed, there is much empirical evidence which documents that the variability of stock returns after annual and interim earnings announcements is abnormal high (e.g. Beaver 1968, May 1971). Transient behavior can be found in reality.

5. RELEVANCE

We suppose the results to offer some new insights for theory and practice. Up to now, research seems to believe that a reduction of the information asymmetry between ordinary traders and firms, without a doubt, would improve market efficiency (e.g. Lev, 1992). Our dynamic analysis could prove that this relation does not hold necessarily.

In practice private as well as public institutions could benefit from these results. First, the findings are relevant for corporate information disclosure strategy[19]. Several studies report that firms disseminate good news more often than bad news (e.g. Pastena and Ronen, 1979; Kross and Schroeder, 1984; Dye and Sridhar, 1995). In general, firms have been observed to voluntarily disclose value-relevant information quite rarely. We assume that firms are interested in keeping the volatility of its stock prices low in order to achieve high calculability and suggest stability to the public. If so, holding back information may be risky. Suppose that with the next regular report the withheld information come out all together. Then, the batch of news reaching traders could push the dynamics of prices in a phase of high volatility.

Second, disclosure regulation setters may regard the results with respect to market distortion as a direct indicator of market efficiency. The common belief is that strict disclosure requirements warrant liquid and efficient markets and reduce the cost of capital for firms. Admati and Pfleiderer (2000) prove that a tightening of disclosure regulations can be welfare beneficial. However, it may be difficult to identify the precise regulation to exploit the positive potential. Moreover, there are cases in which stronger regulation is harmful since corporate costs of disclosure exceed the public benefit. Our analysis confirms and amplifies the findings. ‘Forcing firms to talk’ more often may be efficiency-improving, and thus,

[19] For a survey of corporate disclosure strategy see Lev (1992).

welfare-improving, yet sometimes welfare shrinks. The conclusion holds beyond disclosure costs.

6. CONCLUSION

Our study has demonstrated that the effects of temporal information gaps on market efficiency are far from straightforward. While we supposed longer temporal information gaps to deteriorate market efficiency, the analysis has shown that the relationship may sometimes be the other way around. The simulations have demonstrated this for market efficiency in the semistrong and in the strong form. The surprising results could be explained by the relationships between temporal information gaps and the noise affecting the dynamics. Extensive gaps lead to fewer but heavier shocks. Overall the average noise level declines. The changes in noise influence market volatility. Subjective market distortion (semistrong market efficiency) directly results from volatility. The relationship between information gaps and objective market distortion (strong market efficiency) is determined by volatility and by the discrepancy between subjective perception and true fundamental value. If average volatility declines consequent to an extension of the temporal information gap, the negative effect of the increased perception bias is sometimes offset. As a result, market efficiency, even in its strong form, may improve when the temporal information gap is prolonged. The abnormal finding is especially likely, if retaining news tranquilizes market volatility relatively well.

In general, our study supports the notion of price adjustment and value discovery as complex processes. While the configuration of value discovery represented the depended variable, the complexity of the adjustment process turned out to arise endogenously by the presence of different trading strategies. We could observe that arbitrage implicates the intense interaction of traders over a certain span of time. During the phase of adjustment the market can be highly volatile. In this sense the mechanism of arbitrage itself may temporarily trigger, instead of removing, inefficiency.

We believe that there is still need for investigation on the topic. While our model driven approach contributed to uncover the complex aspects of the relationship between temporal information gaps and market efficiency, future research should identify how likely the different scenarios might be for reality. We hope our study will motivate successive projects in this area.

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2

Disclosure Requirements, the Release of New Information and Market Efficiency: New Insights from Agent-based Models

Oliver Hermsen, Björn-Christopher Witte, Frank Westerhoff

Abstract: We explore how disclosure requirements that regulate the release of new information may affect the dynamics of financial markets. Our analysis is based on three agent-based financial market models that are able to produce realistic financial market dynamics. We discover that the average deviation between market prices and fundamental values increases if new information is released with a delay, while the average price volatility is virtually unaffected by such regulations. Interestingly, the tails of the distribution of returns become fatter if fundamental data is released less continuously, indicating an increase in financial market risk.

Keywords: Agent-based financial market models; market efficiency; release of new information; disclosure requirements; regulation of financial markets; Monte Carlo analysis.

JEL classification: G14; G18.

1. INTRODUCTION

A key characteristic of financial markets is the recurring emergence of severe bubbles and crashes. During such turbulent market dynamics, public debate about a better regulation of financial markets usually flares up. However, the design of more stable financial markets is an intricate issue. For instance, empirical studies are often difficult to conduct since data to evaluate new policy regimes may simply be non-existent. Alternatively, realistic financial market models are required to stress test new policy measures.

Fortunately, such models have appeared recently in the form of agent-based financial market models. For surveys of this burgeoning field of research, see, for instance, LeBaron (2006), Chiarella et al. (2009), Hommes and Wagener (2009), Lux (2009) and Westerhoff (2009). In these models, boundedly rational traders rely on simple heuristic strategies, mainly technical and fundamental trading rules, to determine their investment positions. Simulations reveal that (nonlinear) interactions between heterogeneous market participants can create complicated asset price dynamics. Some of these models are even capable of producing artificial time series that have similar statistical features to actual financial market data (see, e.g. Chen et al. 2009). For instance, these models can generate bubbles and crashes, excess volatility, fat tails for the distribution of returns, uncorrelated price changes and volatility clustering.

A number of contributions have already been published where such models are used as computer platforms to evaluate certain policy measures. For instance, Westerhoff (2003) explored the consequences of trading halts, Scalas et al. (2005) insider trading and fraudulent behavior, He and Westerhoff (2005) price caps, Wieland and Westerhoff (2005) central bank interventions, Westerhoff and Dieci (2006) transaction taxes, Brock et al. (2009) hedging instruments, Hermsen (2010) Basel II regulations for market risk and Thurner et al. (2009) leverage effects. All in all, these approaches seem to enable us to improve our understanding of how certain regulatory policy measures function (for a survey, see Westerhoff 2008).

The focus of this paper is on disclosure requirements. One important aspect in the design of disclosure rules is how frequently firms should report new information about their business condition to the general public.[20] For instance, should firms inform investors

[20] A recent example where this issue has controversially been discussed is the secret rescue of the RBS and HBOS by the Bank of England. Both banks received huge loans by the Bank of England in October and November 2008. However, these loans were made public only one year later in November 2009. The motivation for this "period of non-disclosure" was to prevent an immediate adverse impact on consumer confidence and a consecutive bank run (BBC 2009, The Economist 2009).

continuously or would it be better to inform them less frequently? An argument in favor of the first view could be that changes in the firms' fundamental values then emerge less abruptly. Moreover, the informational content of market prices may increase. Support for the second view could be based on the fact that good and bad new information may cancel each other out over time, making the evolution of the firm's fundamental values appear more stable. Also the information processing capabilities of market participants may be limited and a constant flow of new information may simply overburden them.

To explore the relationship between disclosure requirements, the release of new information and market efficiency, we use three different agent-based financial market models, namely the models of Lux and Marchesi (1999, 2000), Chiarella et al. (2006a, b) and Franke and Westerhoff (2009, 2011). All these models are able to match, at least approximately, the stylized empirical facts of financial markets. We use the above models with the settings originally proposed. The only component we modify is the market participants' perception of the fundamental value. Our key conclusion is that market efficiency may benefit from a more continuous release of new information. In all three models we observe on average that prices are closer to fundamental values if investors are informed promptly about changes in a firm's economic performance. Although the price variability is virtually unaffected by this regulatory measure, financial market risk may nevertheless increase if new information becomes delayed. We find that the tails of the distribution of returns contain more probability mass in the event of a delayed release of new information. Put differently, the average price variability may remain constant but the distribution of returns changes such that more extreme price changes emerge. Given that extreme returns constitute a large part of financial market risk, policy makers may wish to prevent this. A (preliminary) policy recommendation is therefore that firms should disclose new information continuously.

Our paper is organized as follows. In Section 2, we illustrate how disclosure requirements may affect the perception of fundamental values and introduce measures to capture market efficiency. In Section 3, we recall three agent-based financial market models and discuss their dynamics, both with an immediate and delayed update of fundamental values. In Section 4, we conduct a Monte Carlo analysis to systematically investigate the relation between disclosure requirements and market efficiency. The last section concludes.

2. THEORETICAL BACKGROUND

Let us start with the theoretical background relevant to our analysis. In Section 2.1, we first introduce the concept of temporal information gaps and suggest how they can influence market efficiency. In Section 2.2, we present a number of measures to evaluate market efficiency.

2.1 Temporal Information Gaps and Market Efficiency

The fact that information about the economic and financial conditions of firms is released only at discrete time steps produces what Witte (2009) terms temporal information gaps (TIGs). Technically speaking, a TIG can be defined as the time span from one period of publication of new information to the next. TIGs can cause market participants to be not up-to-date about a firm's true fundamental values, even if they are perfectly rational.

To capture the discrepancy between the true fundamental value and traders' perception of it, one can differentiate between the subjective fundamental value and the objective fundamental value. Under the assumption that new information appears randomly, the objective fundamental value, i.e. the true value, follows a random walk. The subjective fundamental value, i.e. traders' opinion about the true value, is constant as long as traders do not receive any new information. However, every time new information is published agents can – in principle – discover an asset's true value, such that the subjective fundamental value adapts to the objective one. The objective fundamental value then drifts away from the subjective one, until the next release of new information.

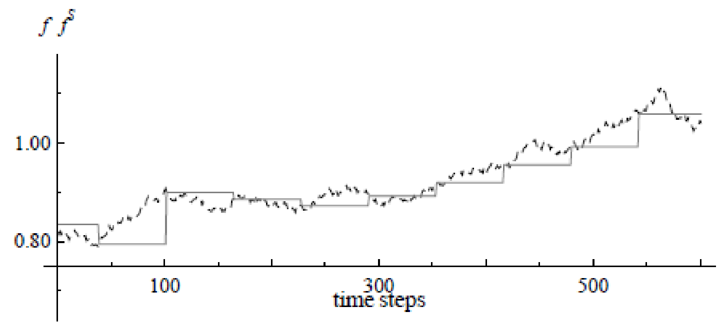

Figure 1: Relation between the objective and subjective fundamental value. The figure shows the evolution of the objective fundamental value (dashed line) and the subjective fundamental value (solid line) for a TIG of 63 days (approximately a quarter of a year).

Figure 1 illustrates this behavior for a TIG of 63 periods, which corresponds approximately to a quarterly publication frequency. The objective fundamental value (dashed line) evolves in the form of a random walk (new information arrives every period and is normally distributed with mean zero and constant standard deviation). Every 63 periods, agents get to know the true value such that subjective fundamental values (solid line) and objective fundamental values correspond. Otherwise, the subjective value remains unchanged and starts to deviate from the true value.

In general, the relationship between TIGs and different indicators of market efficiency appears to be ambiguous. Firstly, longer TIGs obviously increase the discrepancy between the subjective and objective fundamental value. Therefore, longer TIGs can be expected to increase the deviation between market prices and objective fundamental values. Secondly, TIGs influence the overall noise level impacting on price dynamics, since every release of new information represents an exogenous shock for market participants. There are three important effects to consider.[21] Every quadruplification of the TIG quarters the number of shocks in a finite span of time (effect 1), doubles the average size of the shock once a shock occurs (effect 2), and halves the average noise level, interpreted as the mean shock averaged over all periods (effect 3). These different effects influence the price dynamics. Nonetheless, the precise result is hard to foresee. Whereas effects 1 and 3 tend to stabilize market dynamics, effect 2 is presumably destabilizing. Due to these rival effects, we use agent-based models to explore the relationship between TIGs and market efficiency.

2.2 Measures of Market Efficiency

Considering relevant measures to characterize important aspects of financial market efficiency, we have to consider several aspects. On the one hand, prices should be close to fundamental values. On the other hand, price variability should be low. In particular, extreme price changes, which constitute a large part of financial market risk, should be rare.

Based on the distinction between the objective and subjective fundamental value, we can discriminate between two types of distortion. Objective distortion D^O captures the deviation of objective fundamental value f_t and market price p_t as follows:

$$D^O = \frac{1}{T}\sum_{t=1}^{T} |ln\, p_t - ln\, f_t| \tag{1}$$

where T is the number of observations in a given sample. A higher objective distortion obviously indicates that the market prices contain less information about the asset's true fundamental value.

The subjective distortion D^S takes the subjective fundamental value f_t^S into account. Hence,

$$D^S = \frac{1}{T}\sum_{t=1}^{T} |ln\, p_t - ln\, f_t^S| \tag{2}$$

[21] We assume that the objective fundamental value follows a random walk. For a derivation of the quantitative relationships, see Witte (2009).

Subjective distortion measures the deviation from the market price and the subjective fundamental value, and may thus be regarded as the distortion perceived by market participants.

Let us define returns as the log price change, i.e. $r_t = \ln p_t - \ln p_{t-1}$. We can then measure volatility by the square root of the average return

$$V = \sqrt{\frac{1}{T}\sum_{t=1}^{T} r_t{}^2} \qquad (3)$$

An increase of V indicates an increase in the variability of prices and is thus an indicator of financial market risk.

As a second measure of financial market risk we consider the tail index of the distribution of returns. According to the Hill estimator (Lux and Ausloos 2002), this tail index can be calculated as follows. The absolute returns of a sample are first arranged in descending order $|r_L| > |r_{L-1}| > \cdots > |r_{L-k}| > |r_1|$. The number of observations in the tail of the sample is denoted by k. The tail index is then obtained by

$$\alpha^H = \left(\frac{1}{k}\sum_{i=1}^{k} ln(|r_{L-i+1}|) - ln(|r_{L-k}|)\right)^{-1} \qquad (4)$$

Usual tail fractions are 2.5% and 5%. A lower α^H indicates more probability mass in the tails of the distribution of returns and thus the presence of more extreme returns. Contrary to the volatility measure (3), measure (4) thus focuses explicitly on extraordinary events.

3. Description and Dynamics of Models

We next present a brief informal outline of a number of relevant aspects regarding the models used in our study. For a detailed description, we refer to the respective literature. All the models considered are able to mimic important stylized facts of financial markets. At the moment it is not clear which of the three models replicates the statistical features of actual asset prices best. Another reason for using three different agent-based models is to check whether our main results display some robustness. A comprehensive survey of the potential of agent-based models to explain the stylized facts of financial markets is provided by Chen et al. (2009). Since we wish to explore the effects of temporal information gaps, we particularly focus on the implementation of the objective and subjective fundamental value.

3.1 Lux and Marchesi's Model

Lux and Marchesi's model (1999, 2000) contains a large number of interacting agents which fall into three groups: fundamentalists, optimistic chartists, and pessimistic chartists. The agents switch between these groups and, since this model is constructed in continuous time, they can do this several times a day. Profits are decisive for agents to switch between the groups of chartists and fundamentalists. Fundamentalists believe that the market price will revert to the fundamental value. The higher the discrepancy between the market price and fundamental value, the higher the expected profits of fundamentalism. Chartists extrapolate recent market price changes. Their actual profits are generated by short-term capital gains earned by price changes (or losses sustained by price falls). Fundamentalists' expected profits and chartists' actual profits are compared. They govern agents' switching behavior with respect to the two trading philosophies.

Whether a chartist is optimistic or pessimistic depends on two factors: the recent market price trend and the opinion index. This index measures the mood of the majority of chartists, thus taking into account herding behavior among agents. Both factors are combined in a function that determines switches from one group of chartists to the other. If both factors point in the same direction, such as a price increase together with a dominance of optimistic chartists, this is regarded as a strong indication of a continuing price increase. It is then likely that the number of optimistic chartists will increase. Price changes are realized by a market maker according to excess demand generated by traders (plus a normally distributed noise term).

The fundamental value in Lux and Marchesi (1999) is defined as a random walk. Its discrete time version reads

$$log(f_{t+1}) = log(f_t) + \sigma\varepsilon_t, \tag{5}$$

with $\varepsilon \sim N(0,1)$. Here and in the following we regard one time step as one day.

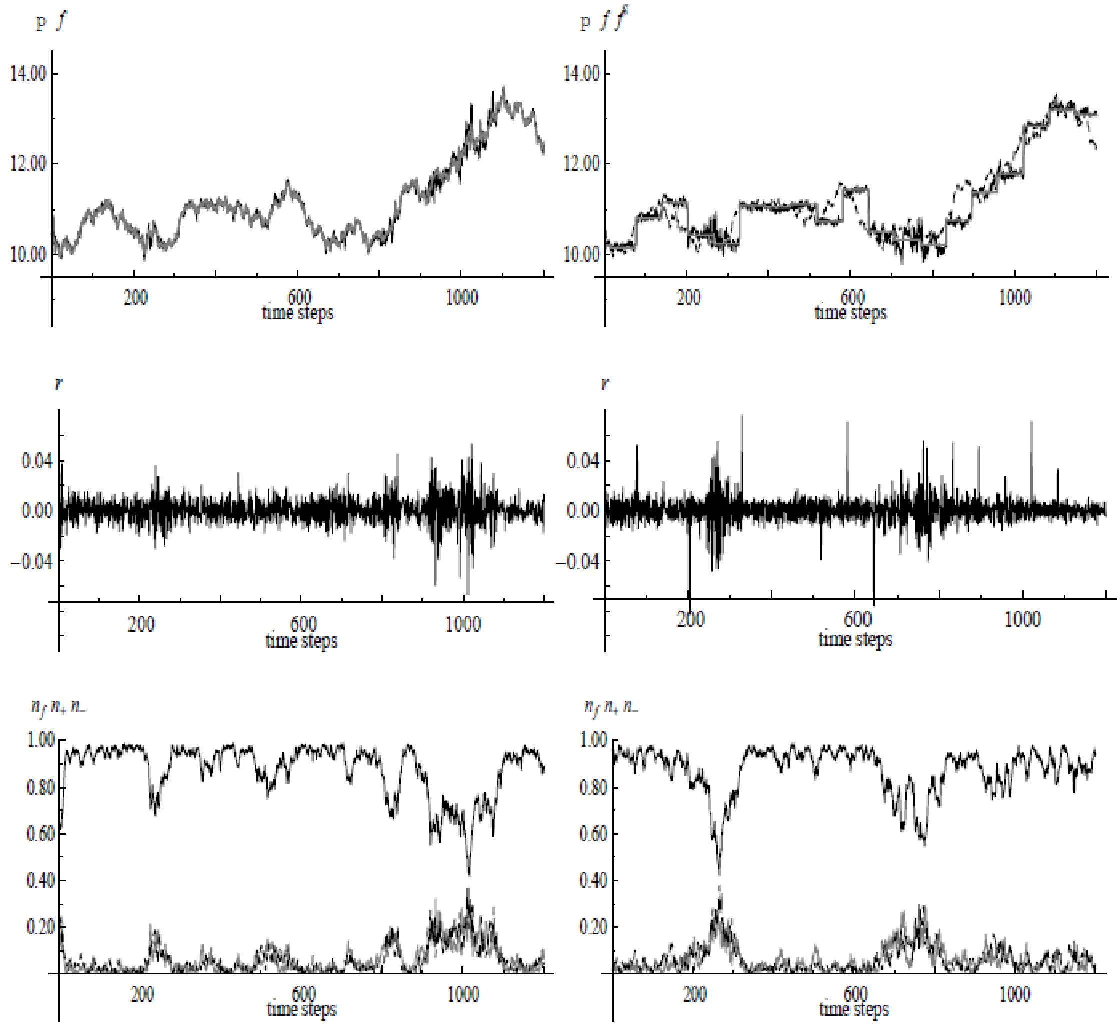

Figure 2: Dynamics of Lux and Marchesi's model. Left panels from top to bottom: the market price (black solid line) and the objective fundamental value (dashed line) for the basic model; returns; proportions of fundamentalists (black solid line), pessimistic chartists (gray solid line), and optimistic chartists (black dashed line). Right panels: identical to the left panels, albeit for a TIG of 63 days. The upper right panel also contains the subjective fundamental value (gray solid line).

Figure 2 gives an impression of the resulting dynamics.[22] The left panels of Figure 2 provide a representative simulation run of the basic model. The top and middle panels show a price and return time series for 1200 days. Note that the market price tracks the objective fundamental value quite closely. Moreover, there are significant volatility outbursts (e.g. around time steps 1000). In periods of high volatility, we find a decrease in the fundamentalists' fraction (n_f) and an increase in the optimistic and pessimistic chartists' fractions (n_+ and n_-), as the bottom left panel shows. Put differently, an increase in the use of chartists' strategies causes an increase in volatility.

[22] Lux and Marchesi (2000) use four different parameter sets in their paper. We use their "set II", which is characterized as quite realistic concerning the stylized facts of financial markets. Similar results are obtained for other parameter sets. See also Alfarano and Lux (2007) for useful details about the simulation algorithm.

Instead of the objective fundamental value, in our experiments we use the subjective fundamental value f_t^S, defined as

$$f_t^S = \begin{cases} f_{t-1}^S, & if \quad t \notin k * TIG \\ f_t, & if \quad t \in k * TIG \end{cases}, \tag{6}$$

with $k \in \{1, 2, 3, ...\}$ and $TIG \in \{1, 2, 5, 10, 15, 21, 25, 30, 63, 100, 250\}$. For any integer time step that is a multiple of a given TIG, the subjective fundamental value is updated to the objective fundamental value. For other time steps, the subjective fundamental value remains constant.

While the left panels of Figure 2 visualize aspects of the model with $TIG = 1$ (the fundamental value is updated on a daily basis and is thus perceived correctly), the right panels describe the dynamics of the model when new information is published quarterly ($TIG = 63$). Note that the market price is now close to the subjective fundamental value and may differ from the objective fundamental value. This is contrary to the basic model. As can also be seen, some of the extreme price movements occur simultaneously with the release of new information.[23] Note also that volatility outbursts appear at quite different periods, although we use the same seed of random variables in the two simulation runs. From inspecting individual time series it is thus hard to say whether different TIGs stabilize or destabilize financial market dynamics.

3.2 Chiarella, He and Hommes' Model

The asset pricing model of Chiarella, He and Hommes (2006a, b) is ruled by excess demand of a risky asset generated by fundamentalists' and chartists' trading rules. The more the market price is above (below) the fundamental value, the stronger the fundamentalists' intention to sell (buy) the risky asset, since they expect a price correction. The chartists' excess demand depends on a 100-day moving average rule (MA). If the market price is above (below) this MA, chartists buy (sell) the risky asset. The fractions of chartists and fundamentalists are modeled via a discrete choice model, where the corresponding fitness functions depend on realized net profits. A market maker changes prices with respect to the excess demand of chartists and fundamentalists. Moreover, the price adjustment is distorted by a normally distributed noise term.

The random walk of the fundamental value is modeled in Chiarella et al. (2006a)[24] as

[23] The reason for this is as follows. If fundamentalists realize that the price of an asset has disconnected from its fundamental value, they place larger orders which, in turn, cause larger price adjustments.

[24] We use the parameter setting given in Figure 3 of Chiarella et al. (2006a), since this setting is able to mimic the stylized facts of financial markets best.

$$f_{t+1} = f_t(1 + \sigma\varepsilon_t) \quad (7)$$

with $\varepsilon \sim N(0,1)$. The subjective fundamental value f_t^S is again defined as in (6).

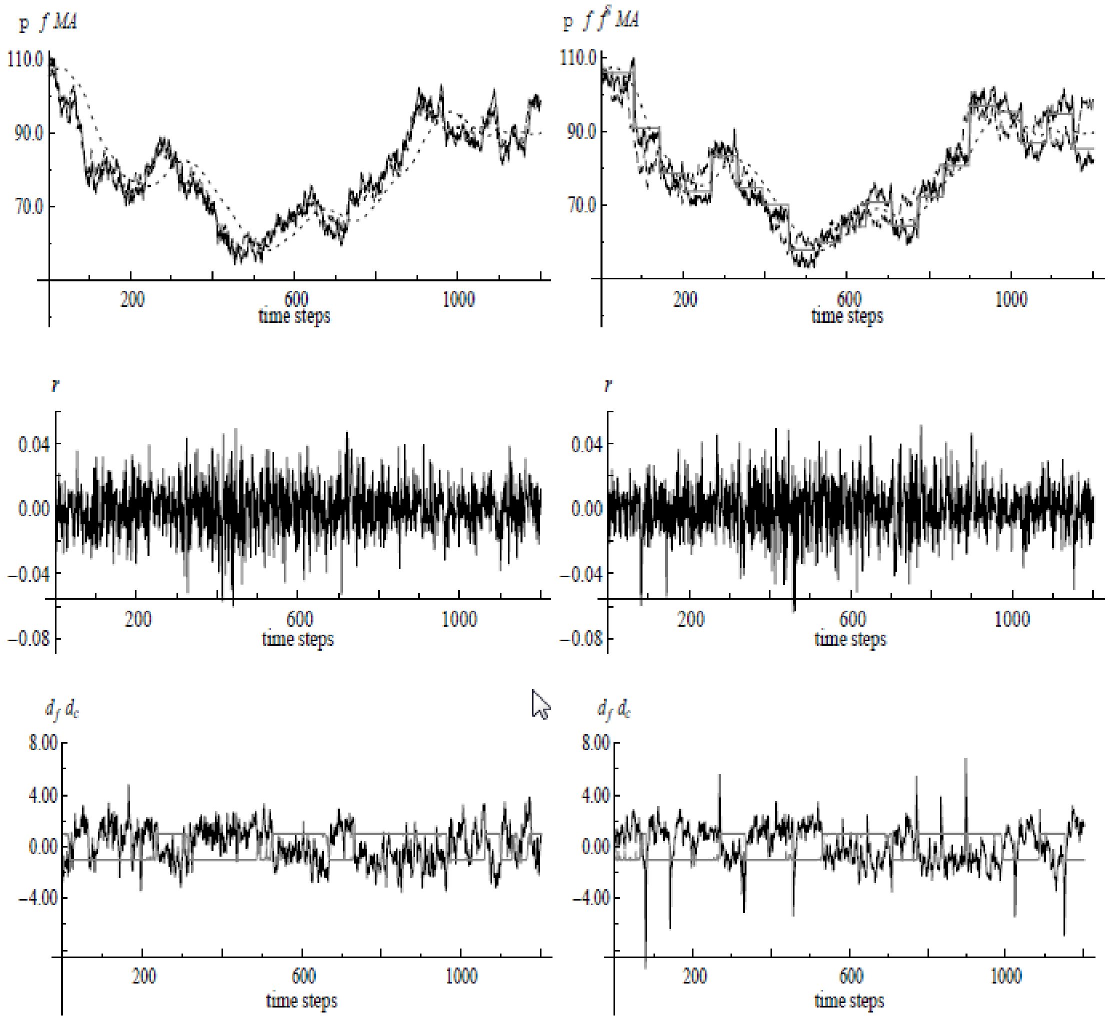

Figure 3: Dynamics of Chiarella, He and Hommes's model. Left panels from top to bottom: the market price (black solid line) and the objective fundamental value (dashed line), and 100 day moving average (dotted line) for the basic model; returns; excess demands of chartists (gray solid line) and fundamentalists (black solid line). Right panels: identical to the left panels, albeit for a TIG of 63 days. The upper right panel also contains the subjective fundamental value (gray solid line).

Figure 3 illustrates the dynamics for this model in the same way as Figure 2. Instead of the agents' fractions, we find, however, the excess demands of fundamentalists and chartists (d_f and d_C) in the bottom panels. The chartists' excess demand is positive if the 100-day MA is above the market price (and vice versa, of course). The fundamentalists' excess demand is more volatile, and a factor that causes extreme returns. In particular, the right bottom panel highlights this observation for the quarterly updated subjective fundamental value ($TIG = 63$). Strong price changes occur simultaneously with high absolute excess demand of fundamentalists at time periods when the fundamental value is revealed. Different price levels are one reason for the volatility cluster, as the top and middle panel both reveal. For lower price levels (time steps around 450), returns are on average higher than usual.

As already mentioned, the right panels of Figure 3 describe a situation for a quarterly updated fundamental value. Compared to the dynamics of the model by Lux and Marchesi (Figure 2), the market price is pushed away from both the objective and subjective fundamental value more strongly. However, the deviation between the market price and subjective fundamental value is still rather low compared to the deviation between the market price and objective fundamental value, and to our findings from the next model.

3.3 Franke and Westerhoff's Model

Franke and Westerhoff's model (2009, 2011) contains two different groups of speculative traders: chartists and fundamentalists. Agents following fundamentalists' trading rules buy (sell) assets if the market price is below (above) the fundamental value; agents following chartists' trading rules extrapolate recent price trends. Both demand functions are buffeted by exogenous noise. A combination of predisposition towards chartism, herding effects and current market conditions is decisive for transitions between the two groups. The agents' herding behavior is formalized via a majority index x, which is bounded between -1 (all agents are chartists) and +1 (all agents are fundamentalists). The probability of a trader being a fundamentalist increases with the majority index and the observed distortion in the market. To be precise, the higher the fraction of fundamentalists and the higher the mispricing in the market, the greater the probability that an agent will use a fundamental trading rule. Finally, a market maker adjusts prices with respect to excess demand.

The fundamental value is assumed to be constant in this model. To investigate the effects of a deviation between the objective and subjective fundamental value, we assume (5) for the fundamental value (instead of $\ln(f_{t+1}) = \ln(f_t)$, as defined in Franke and Westerhoff 2009).[25]

[25] This requires a new assumption about the standard deviation of the news process. We take here the same value as in Lux and Marchesi (1999, 2000), i.e. we set the daily standard deviation to $\sigma = 0.005$. The other model parameters are as in Franke and Westerhoff (2009a, b).

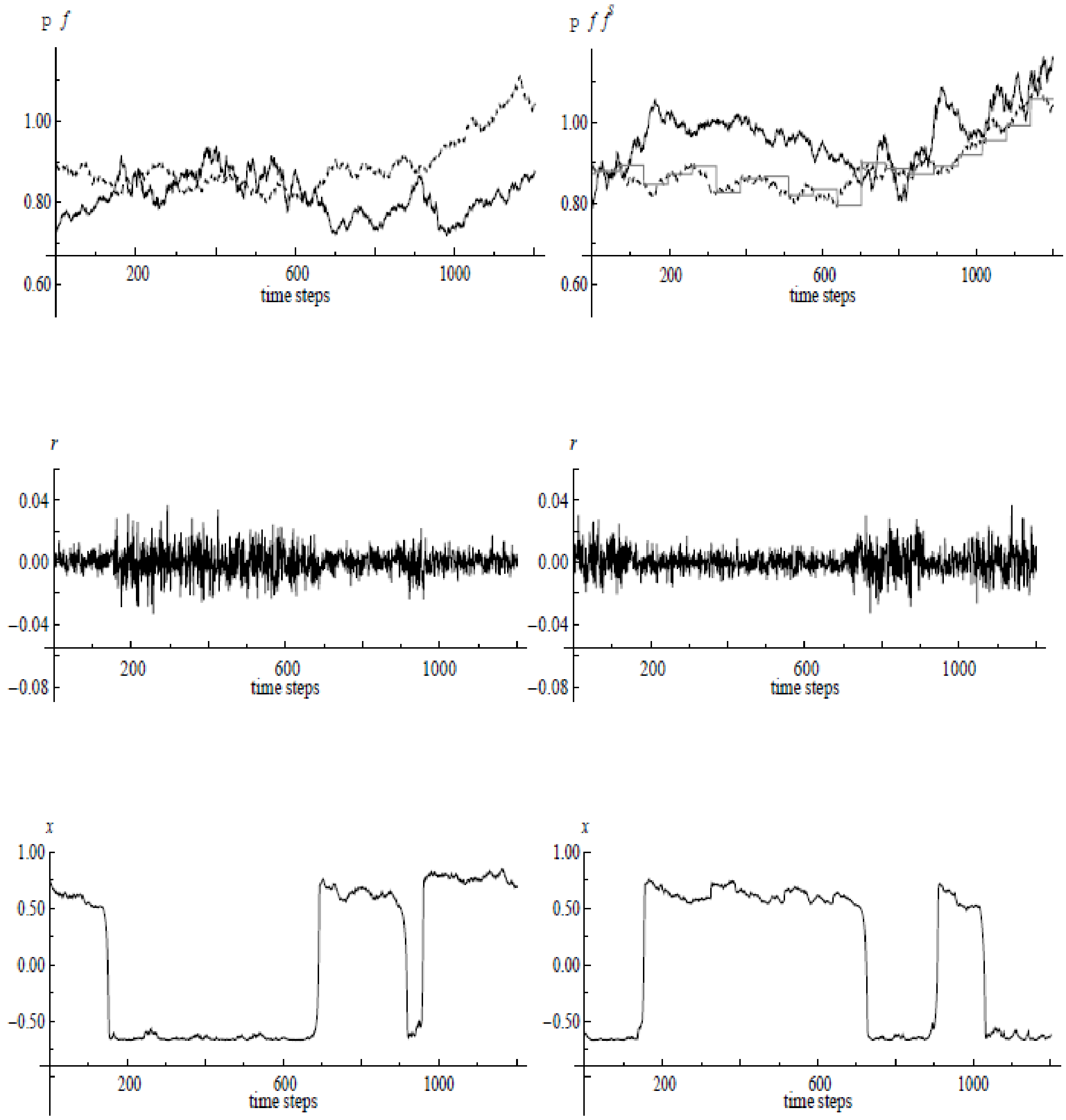

Figure 4: Dynamics of Franke and Westerhoff's model. Left panels from top to bottom: the market price (black solid line) and the objective fundamental value (dashed line) for the basic model; returns; development of the majority index (x < 0: majority of chartists; x > 0: majority of fundamentalists). Right panels: identical to the left panels, albeit for a TIG of 63 days. The upper right panel contains the subjective fundamental value (gray solid line).

Figure 4 is constructed analogously to Figures 2 and 3. As we can see, the model is able to replicate profound volatility clustering. Volatility outbreaks can be found around time step 400 for the basic model (left panels, daily update of objective fundamental value) or around time step 800 for the modified model (right panels, quarterly update of objective fundamental value). Volatility clusters occur simultaneously with a high proportion of agents following chartists' trading rules, as depicted in the bottom panels. Negative values for the majority index signal a dominance of chartism. For periods with a positive majority index, fundamentalists govern the dynamics, and volatility is lower.

Concerning the development of the market price and the objective fundamental value, the top left panel of Figure 4 ascertains that the deviation between the market price and fundamental value is already quite significant in the basic model. The top right panel indicates that this deviation does not change much if new information is revealed on a quarterly basis. This is a clear difference compared to the previous models, where we observe a higher deviation between market price and fundamental value compared to the basic model in the left panels, especially for $TIG = 63$ (see Figures 2 and 3). Again, we observe that volatility outbursts occur in quite different periods for the selected TIGs.

4. A MONTE CARLO ANALYSIS

Now we systematically explore how different TIGs affect the dynamics of the agent-based models presented so far. In Section 4.1, we first clarify the simulation design. In Sections 4.2 to 4.4, we turn to a general analysis of the three models.

4.1 Simulation Design

Our numerical results with respect to our four market efficiency measures are based on 500 time series (each with 5500 observations) for each TIG. For the TIGs, we choose 1 (daily publication), 2, 3, 4, 5 (weekly publication), 10, 15, 21 (monthly publication), 25, 30, 63 (quarterly publication), 100, and 250 (yearly publication). Figures 5 to 7 contain boxplots for the following market efficiency measures: objective distortion, subjective distortion, volatility, and tail index. Besides the 25% and 75% quantiles and the median, we also indicate the range of the minimum and maximum value for the 500 time series considered. Moreover, the black dots represent the means of the respective market efficiency measures.

4.2 Insights from Lux and Marchesi's Model

Figure 5 depicts the market efficiency measures for Lux and Marchesi's model. We do not observe any significant influence of the TIGs on volatility. On the other hand, the tail index changes considerably.[26] For TIGs from 1 to 63 periods, the tail index declines steadily before rising again. Note that 63 periods correspond to a quarter of a year – the regular publication frequency applicable, for instance, to firms listed in the German stock market index DAX. Accordingly, the model suggests that the actual regular publication frequency in Germany produces the worst tails in the distribution of returns. The decline in the tail index for TIGs

[26] Hence, return time series with "identical" volatility may nevertheless display different return dynamics. For instance, a return time series with more extreme returns may also have more lower returns so that the net effect on volatility is balanced.

from 1 to 63 periods can be explained as follows. Extensive TIGs lead to large corrections of the subjective fundamental value, which, given that prices track fundamental values closely in this model, trigger large price movements. What causes the rise of the tail index for TIGs from 63 to 250 periods? As TIGs become extensive, corrections of the subjective value become seldom. Thus, heavy adaptive movements of prices occur less frequently.

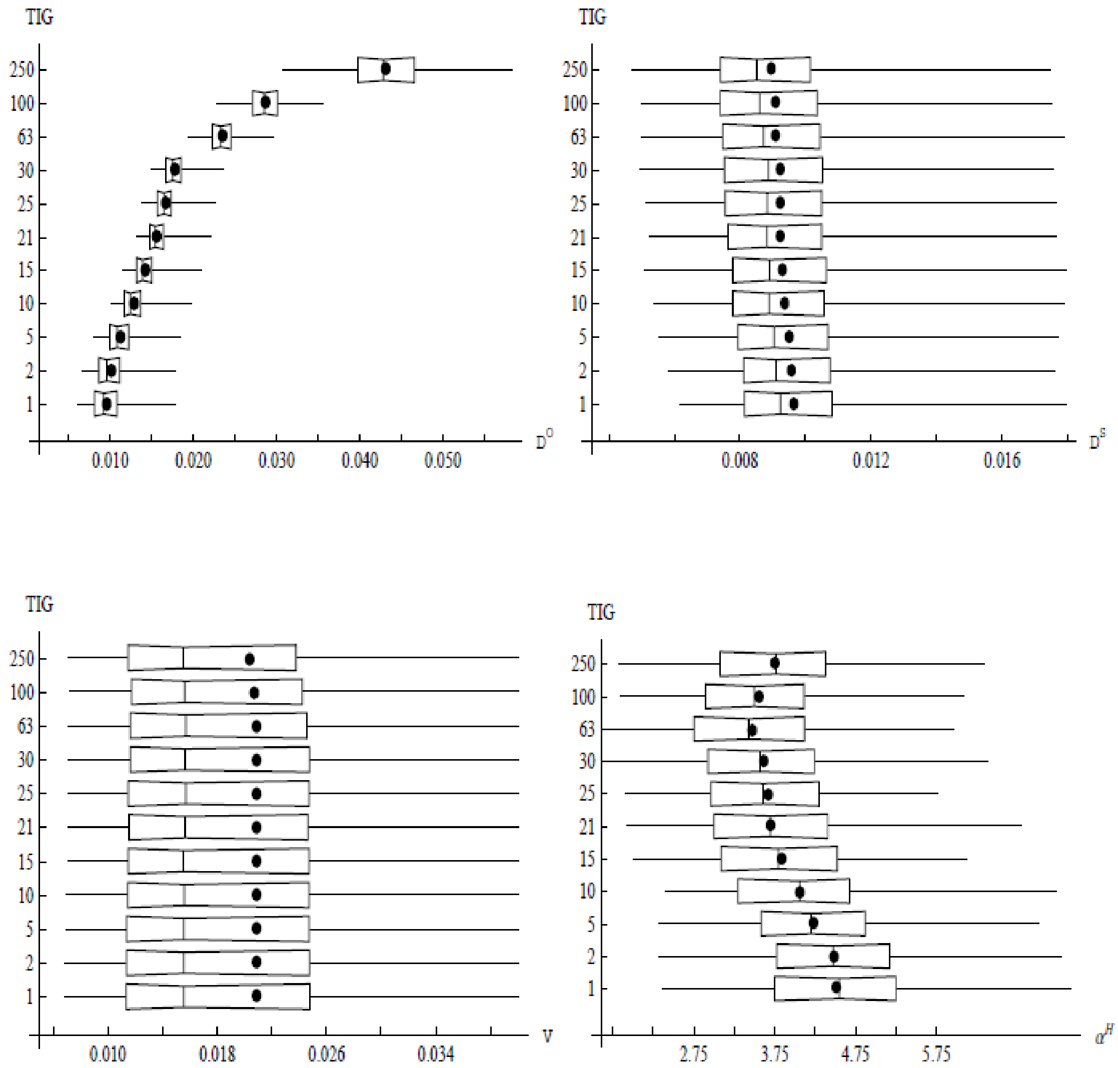

Figure 5: Market efficiency measures for Lux and Marchesi's model. Top left: objective distortion; top right: subjective distortion; bottom left: volatility; bottom right, tail index. The box of the box plots represents the 25% and 75% quantile, the horizontal line represents the range of the minimum and maximum of all 500 time series. The mid vertical line represents the median, whereas the black dot is the mean of the average volatility.

For the remaining measures we observe that TIGs have a negative effect on the objective distortion but do not influence the subjective distortion. This finding is in accordance with the insight that the discrepancy between the subjective and objective fundamental value tends to rise if TIGs increase. Market prices remain close to the subjective fundamental value but not to the objective one.

4.3 Insights from Chiarella, He and Hommes' Models

The efficiency measures for the model of Chiarella et al. are shown in Figure 6. Again, we do not observe any significant effect of TIGs on volatility. In contrast, the tail index decreases continuously, indicating longer TIGs to provoke heavy movements of prices. In comparison to Lux and Marchesi's model, the decline in the tail index is slightly smaller. The reason for this is that the dynamics of prices in the model of Chiarella et al. are less dependent on the evolution of the objective/subjective fundamental value than in Lux and Marchesi's model. Thus, corrections of the subjective fundamental value affect the dynamics of prices less directly. The distortion measures behave similarly to those in Lux and Marchesi's model: longer TIGs have a negative effect on objective distortion but do not significantly influence subjective distortion.

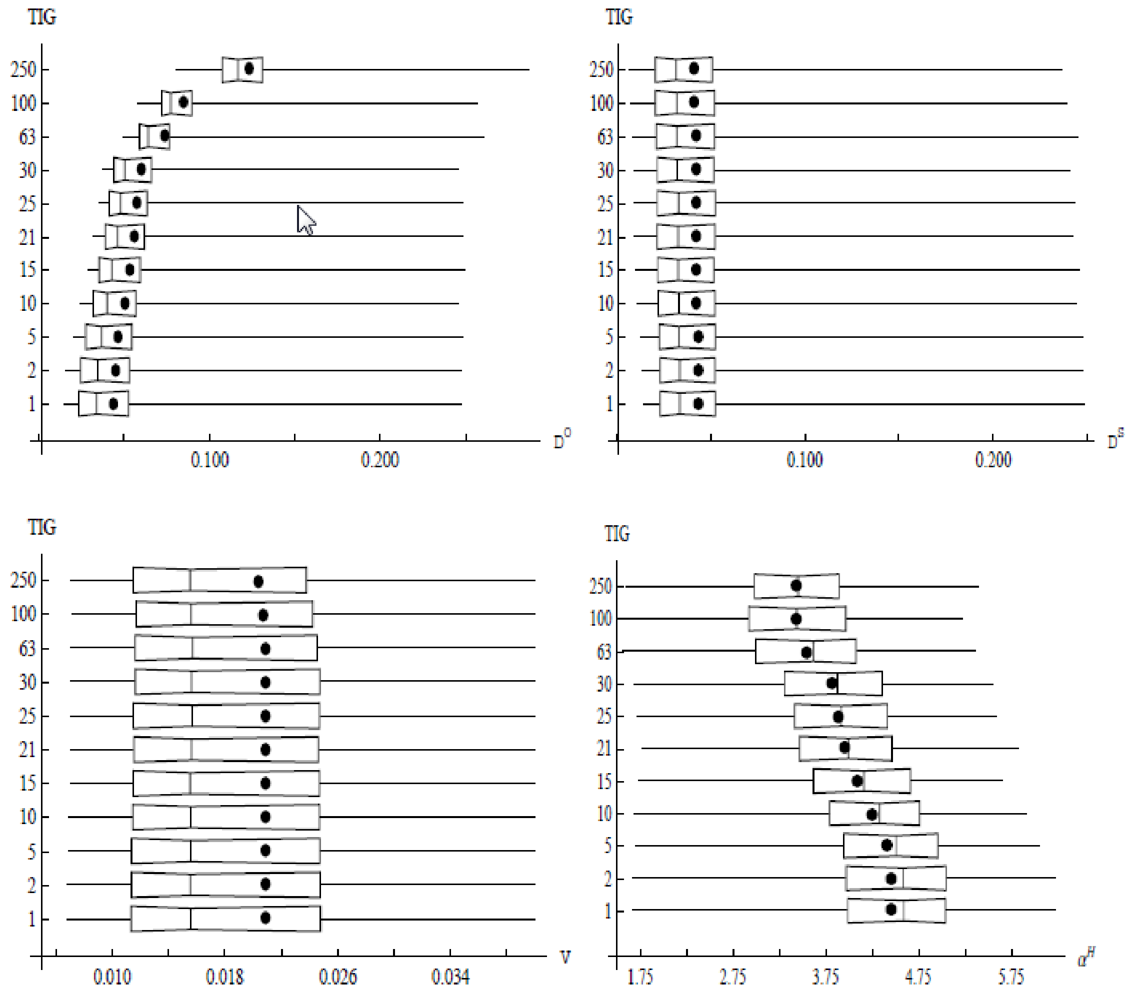

Figure 6: Market efficiency measures for Chiarella, He, and Hommes' model. The same design as in Figure 5, but volatility estimates are only depicted between 0.006 and 0.04

4.4 Insights from Franke and Westerhoff's Model

Results for Franke and Westerhoff's model are depicted in Figure 7. The model confirms the previous finding that TIGs do not influence volatility. However, when it comes to the tail index, the model reveals its special characteristic: in contrast to the previous models, there is no significant influence of TIGs on the occurrence of heavy returns. The reason for this is that in Franke and Westerhoff's model, the market price and fundamental value evolve relatively independently of each other, irrespective of whether they are objective or subjective.[27] Hence, the return distribution hardly changes, even if the corrections of subjective fundamental values become substantial.

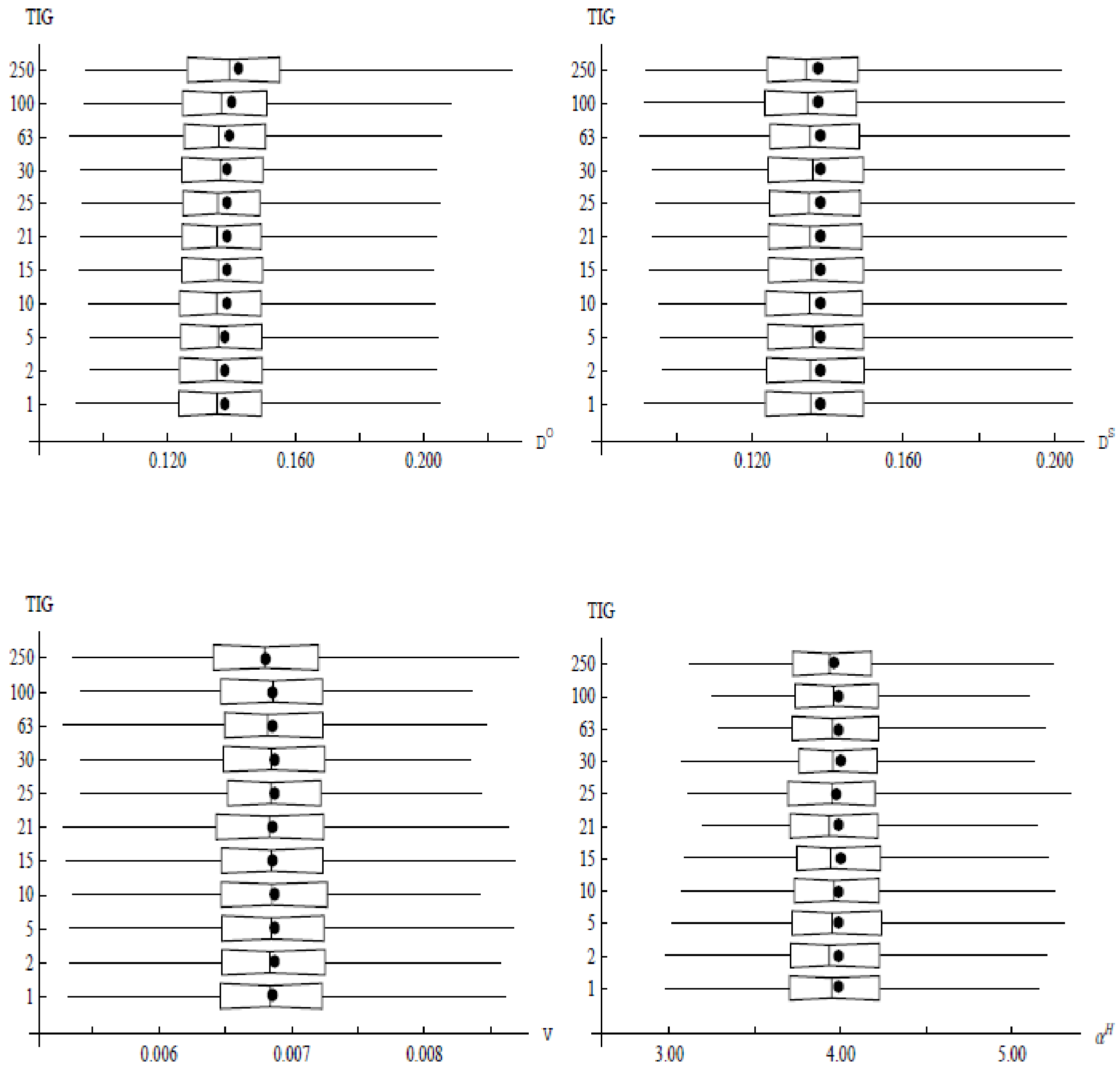

Figure 7: Market efficiency measures for Franke and Westerhoff's model. The same design as in Figure 5.

The individual characteristic of the model dynamics also becomes manifest in the distortion indicators. Compared to the other models, the effect of TIGs on objective distortion is relatively low. The reason for this is that in this model, average objective distortion is

[27] Another prominent agent-based financial market model is that by Gaunersdorfer and Hommes (2007), which was modified and recalibrated recently by Franke (2010). In this Gaunersdorfer-Hommes-Franke model, prices may also significantly deviate from fundamental values. Results with respect to our four market efficiency measures for this model are quite similar to those observed for Franke and Westerhoff's model.

relatively large, even if new information is published instantly. Thus, TIGs cause only a relatively small part of the objective distortion. Regarding subjective distortion, the results of the other models are confirmed. There is no significant relation between TIGs and subjective distortion.

5. CONCLUSIONS

How should policy makers regulate firms' disclosure requirements with respect to the release dates of new information? To answer this question, we use three agent-based financial market models as a computational laboratory. All agent-based models are able to match the stylized facts of financial markets quite well, thus it seems reasonable to employ them in our study. The results we obtain from our Monte Carlo study can be summarized as follows:

- All models suggest that if firms release new information less frequently, the objective distortion increases, i.e. prices fluctuate, on average, more distantly towards their true fundamental values. This effect is more pronounced in models in which prices track their fundamental values more closely.
- In the eyes of market participants, the average perceived deviation between prices and fundamental values, that is the subjective distortion, is more or less constant across different temporal information gaps. This result is confirmed by all three models.
- Different publication frequencies appear to have virtually no impact on volatility. We find that for low, medium and high temporal information gaps, the variability of prices remains essentially constant.
- The latter observation does not, however, imply that financial market risk also remains unaffected. Interestingly, we find that the tail index of the distribution of returns may decrease if the length of the temporal information gap increases. In particular, in the Lux-Marchesi model the probability of extreme returns is maximized if firms release information on a quarterly basis. The effect of the temporal information gap depends on how closely market prices track subjective fundamental values. If market prices are more disconnected from perceived fundamental values, this effect is rather weak. However, if market prices are close to perceived fundamental values, as we would expect in efficient markets, this effect becomes significant.

All in all, we conclude from our experiments that firms should instantly give clear and precise information about their economic performance, at least with respect to market efficiency. Of course, this policy recommendation should be viewed with caution. Our approach may be extended in various directions to check the robustness of our findings:

- A central question is how traders perceive fundamental values in reality. Here we assume that they are able to compute the objective fundamental value once they have all of the relevant information. In reality, however, this may not be true. For instance, traders may use different heuristics to calculate the fundamental value, and thus there may even be coexisting perceptions of fundamental values among market participants.
- Moreover, traders may try to form expectations about the arrival of new information. Suppose that the fundamental value has increased in the recent past. Traders may then believe that this trend will continue, even if fundamental values follow a random walk.
- If a greater length of time elapses between publication dates, market participants may also become nervous because uncertainty regarding the true fundamental value will increase. On the other hand, the amount of information market participants have to process increases if firms continuously inform about their economic conditions.
- We followed the literature and assume that the (objective) fundamental value changes every time step. However, this variable may also be modeled as a Poisson jump process.
- Our attention is on a market with a single risky asset. It would be interesting to see how the dynamics work in a model with multiple assets. Should all firms inform the public about new information simultaneously?
- Note that we take only one dimension of disclosure requirements into account, namely the frequency of news releases. Other dimensions such as the level or the style of disclosure requirements play, of course, also an important role for market stability and may have significant impacts on the firms' financing and investment decisions (see Admati and Pfleiderer 2000, Boot and Thakor 2001, Holmström and Kaplan 2003 and Östberg 2006, among others).

All these aspects reveal that much more work is needed to arrive at a solid policy recommendation. Our paper may be regarded as a start in this direction. Nevertheless, we believe that agent-based financial market models may be used to improve our understanding of how new information should be released. Here we learn that it may be better for market efficiency if firms inform the market about their economic situations continuously.

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3

Fund managers - Why the Best Might be the Worst: On the Evolutionary Vigor of Risk-Seeking Behavior

Björn-Christopher Witte

Abstract: This article explores the influence of competitive conditions on the evolutionary fitness of different risk preferences. As a practical example, the professional competition between fund managers is considered. To explore how different settings of competition parameters, the exclusion rate and the exclusion interval, affect individual investment behavior, an evolutionary model is developed. Using a simple genetic algorithm, two attributes of virtual fund managers evolve: the share of capital invested in a risky asset and the amount of excessive risk accepted, where a positive value of the latter parameter points to an inefficient investment portfolio. The simulation experiments illustrate that the influence of competitive conditions on investment behavior and attitudes towards risk is significant. What is alarming is that intense competitive pressure generates risk-seeking behavior and undermines the predominance of the most skilled. In these conditions, evolution does not necessarily select managers with efficient portfolios. These results underline the institutional need for the creation of a competitive framework in which risk-taking does not provide an evolutionary advantage per se, and indicate measures on how to achieve this.

Keywords: risk preferences; competition; genetic programming; fund managers; portfolio theory

JEL classification: C73; D81; G11; G24

1 INTRODUCTION

Evolutionary selection leads to the predominance of the fittest. However, it is not always clear from the very beginning what the fittest behavior will be. This also applies to the field of economics.

Of course, economics does not refer to evolution in the original sense of the reproduction of the superior and genetic progress between generations. Rather, we assume that selection is conducted by market competition rewarding the best with economic wealth and driving the worst into bankruptcy. To give an example, Milton Friedman (1953, p.23) stated that profit maximization is an "appropriate summary" of the conditions of survival, delivering an exemplar for the assumption that competition would favor agents who behave optimally, or rationally, from the angle of economic theory. Today, there is a myriad of studies, many using modeling techniques, which provide strong evidence that this assumption is sometimes misleading. Schaffer (1989), for instance, shows that Friedman's proposition is not valid, if deviating from profit maximization is less harmful for the firm considered than for its contenders.

The present study is related to the class of evolutionary models in which agents are represented by financial traders and ways of behavior are typically trading strategies. To provide a brief overview, models in this field can be classified into two groups. The first one has been described by Hommes (2001) as *adaptive belief systems* (ABS). ABS are formed by boundedly rational traders having different expectations about the future. Traders select strategies with reference to the utility generated by the rules in the past. Typically, utility is measured by the realized net or risk-adjusted profits produced. Evolution is reflected in the change of fractions of beliefs or strategies in the population of traders. Normally, these strategies are either based on technical or fundamental analysis. One of the most important insights provided by ABS is that under certain conditions, apparently irrational noise traders are able to survive evolutionary competition and attain similar profits as fundamentalists, as demonstrated by Brock and Hommes (1998), DeLong et al. (1990, 1991), and Hommes (2001).

Whereas ABS use to be simulation models, a second group of studies follows a purely analytical approach. Taking a more Darwinian perspective, these studies evaluate the evolutionary fitness of a strategy in terms of its ability to survive market selection in the long run. In Blume and Easley (1992), for instance, this ability is determined by the expected growth rates of the wealth share. Based on this criterion, the authors develop a general equilibrium model of a dynamically complete asset market, in which prices are formed endogenously and the set of strategies available is constant. It is found that, contrary to the common belief, the market does not necessarily select investors with rational expectations. Evstigneev et al. (2002) confirm this result for incomplete markets, and Amir et al. (2005) explore its conditions for general strategies. In contrast, Sandroni (2000) illustrates that rational expectations do prevail if the intertemporal discount factor is equal among agents. The heterogeneity of findings is dissolved by Blume and Easley (2006) who show that for any Pareto-optimal allocation, the selection for or against rational expectations is determined entirely by discount factors and beliefs.

The present article deals with one aspect of behavior which has been vastly ignored in the field of studies described above: differences in risk preferences.[28] Risk preferences are relevant if decisions are to be made under uncertainty, that is, when agents know merely the probabilities of the possible consequences of an action. A large body of experimental evidence has led to the notion that human beings behave in a risk-averse manner (at least when the situation of decision making is about the realization of monetary gains), that is, they prefer to get a definite payoff towards a lottery with an expectation equal to this payoff (Allais 1953; Arrow 1971; Kahneman and Tversky 1979). Economic modelers adopt this finding by using CARA (Constant Absolute Risk Aversion) or CRRA (Constant Relative Risk Aversion) utility functions. Others assume agents to be risk neutral, meaning that they simply seek to maximize expected payoffs. Risk-seeking behavior, however, is usually excluded from consideration.

With regards to the subprime crisis, the exclusion of risk-seeing behavior is not easy to justify. Hoping for supreme returns, professional investors deposited huge amounts of capital in assets whose fundamental value was far exceeded, and appeared not to avoid risk at all. How can that be? The finding that human beings behave in a risk-averse manner depends on the condition that the individuals' goal is to maximize their own utility. However, when being in competition with each other, the criterion of selection is not necessarily individual utility but the payoff per se may be crucial for survival. As a result, risk-seeking behavior should not be excluded ex ante, and we should assume that it is adopted whenever it provides a competitive advantage.

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[28] The interest of such questions, however, is noted relatively early. In his eponymous study on "some elementary selection processes in economics", M.J. Farrell (1970) develops two abstract probabilistic models of an evolutionary asset market, and finds that "a large group of inept speculator will always be present". Having regard to future research, he remarks: "Also interesting, […], is to allow the variance of the probability distribution of the outcome of the gamble to vary independently of expected return and so permit a comparison of the effects of selection on risk-seekers and risk-averters."

Previous research has already delivered several insights on the emergence of different risk-preferences in evolutionary environments. In one of the earliest contributions, Rubin and Paul Il (1979) present a simple, static model in which the goal of individuals is to achieve some threshold income, which is interpreted as the creation of offspring. Rubin and Paul Il argue that, if the functional dependency between evolutionary fitness and individual income is non-linear, maximizing the probability to meet the threshold can lead to a different behavior than maximizing expected income. In particular, if the population is already dense, youngsters are inclined to accept gambles, which might even be unfair.

Robson (1992) assumes individual utility to directly depend on wealth (in a concave fashion) as well as on status, that is, the rank of one individual relative to others (in a convex fashion). Like in Rubin and Paul Il (1979), this implies a non-linear utility function like the convex-concave-convex function discussed in Friedman and Savage (1948). Robson shows that in this setup, individuals may purchase insurance and gamble at the same time. This effect appears if increasing wealth leads to a greater boost of status than losing wealth causes a drawback.

Robson (1996) elaborates another refinement of Rubin and Paul Il (1979) with polygyny. In his model, the threshold is derived from the behavior of females choosing men depending on their wealth. As multiple men are chosen, thresholds arise repeatedly, which produces discontinuities in the fitness function of men. Although the payoff function of men implies risk-aversion, it is shown that risk-taking behavior – the acceptance of fair bets – may emerge with arbitrary extension.

The observation that risk-taking behavior may improve individual chances to survive has coined the term of “gambling for redemption”. Malone (2011) sets this problem in the context of the fear of unemployment. In his model, he assumes a politician who is faced with the possibility of a sovereign default. It is shown that under some conditions politicians are inclined to gamble by initiating policies which increase the variance of outcomes but may decrease the outcome expectation. The conditions are: (i) Default increases the probability of a job loss, and (ii) the rents from the job rise with the output of policies whereas in case of a default a minimum rent is paid which is independent from the magnitude of the default. In combination, (i) and (ii) create a convex utility-function, similar to Robson (1992, 1996).

Gambling for redemption has also been tackled by financial research. Kareken and Wallace (1978) or Diamond and Dybvig (1986), for example, argue that deposit guarantees generate incentives for risk-taking behavior of one asset-owner, which is potentially harmful for other share-owners. Again, this result is obtained by a convexity of the individual payoff-function.

The emergence of risk-taking behavior in the models above stems from the fact that achieving some extra income may produce a jump in utility, which is survival or reproduction, whereas there is "little to lose". In this sense, taking risks per se is rational under some conditions. In contrast, Dekel and Scotchmer (1992) illustrate that evolutionary competition does not necessarily favor rational agents. Their model follows a game-theoretical approach, and evolution is based on the well-known replicator dynamics. The analysis shows that the evolutionary outcome is sensitive to what is inheritable. In particular, if players can only inherit pure strategies, strategies that are never a best reply can persist.[29] We may conclude that rationality might not be a necessary condition for the survival of risk-seeking behavior.

In the present study, the evolutionary fitness of different risk-preferences is investigated by agent-based modeling. Essentially, this leads to a highly dynamic model. A difference to most analytical models is that the threshold income emerges model-endogenously. This allows a complex interplay between the individual behavior towards risk and the outcome needed to survive. One goal is to check if individuals behave as predicted by traditional models, or if the agent-based approach can uncover other relevant phenomena.

The article is divided into two major parts. The first part (section two) represents an abstract, theoretical reflection about the evolutionary potential of risk-seeking behavior. In the second part (section three), we present a practical example of a competitive scenario in which risk-preferences play a central role: the competition among fund managers. To explore this scenario, we construct an evolutionary model, in which agents differ in terms of the risk-return profile of their asset portfolio. Competitive pressure is created by exclusions of the worst performing managers. The discards are then replaced by newcomers, whose investment behavior results from a genetic algorithm. Competition parameters are the interval in which exclusions take place and the share of agents to be excluded. Specific research questions are:

- Will evolutionary competition always lead to the prevalence of agents with efficient portfolios?
- Which portfolios will be fittest under different settings of the competition parameters?

[29] Jones (2001) points out that in reality, irrational behavior might also be a temporal phenomenon, which is "the product of a mismatch between the environment in which the brain evolved and the environment in which the brain now must operate".

Our experiments show that agents tend to build conservative but efficient portfolios if the exclusion rate is low. Agents' risk-aversion becomes less if the exclusion rate rises, and/or if the exclusion interval is prolonged. Notably, if the exclusion rate is high and the exclusion interval is low, agents completely deviate from risk-averse behavior but take great risks, although the additional risk does not improve the expected return of their portfolios. Under these competitive conditions, even agents with inefficient portfolios can survive. These results are alarming as they suggest that intense competitive pressure triggers the acceptance of excessive risk and undermines the prevalence of the most skilled.

2 A THEORETICAL VIEW ON THE EVOLUTIONARY ADVANTAGE OF RISK-SEEKING BEHAVIOR

The rational choice between several actions implies the evaluation of the consequences of the alternatives. In reality, however, individuals usually do not know which consequence an action will have but estimate probabilities about the likelihood of a certain outcome – the decision has to be made "under uncertainty". Decisions under uncertainty are frequent in economic contexts. Calculating the profitability of a potential investment, for example, requires information about the future development of revenues, interest-rates, prices etc. Yet, as respective predictions may be subject to error, the present value of the investment cannot be identified definitely. Nevertheless, existing information can be used to establish a set of possible outcomes and to assign probabilities to each of them. If the set of outcomes is continuous (instead of discrete), the probability distribution over this set is often assumed to follow a normal distribution. The latter applies, for instance, for the future return of asset portfolios (Markowitz 1952, 1959).[30]

Figure 1 shows the probability density functions of two normal distributions (profile 1 and 2). The curves may be interpreted as the payoff profiles of two ways of behavior, or more specifically, of two asset portfolios. The profiles differ in terms of the expected payoff, μ, and the payoff variance, σ^2. Obviously, economic theory would predict that individuals strongly prefer profile 1 towards 2, because 1 affords the better expected payoff ($\mu_1 > \mu_2$) at the lower variance ($\sigma_1^2 < \sigma_2^2$), and subjects are commonly assumed to be risk-averse or risk-neutral. Adopting the latter assumption, portfolio theory (Markowitz 1952, 1959) distinguishes between efficient and inefficient portfolios. Profile 2 represent an inefficient portfolio, defined

[30] Although this is a simplification because financial dynamics reveal power-law behavior which leads to heavier tails of the return distribution than predicted by the normal distribution [15].

as any composition of assets for which there exists an alternative one which offers a better expected payoff without implying a greater payoff variance (here: profile 1).

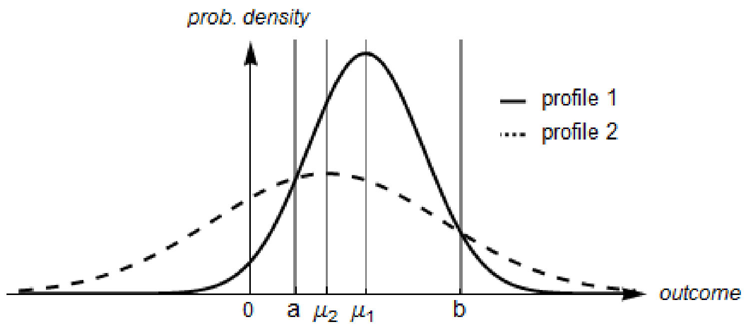

Figure 1: Probability density functions of two alternative behaviors.

From the angle of economic theory, the attractiveness of profile 1 towards 2 seems, therefore, to be evident. From the perspective of evolutionary game theory (Weibull 1997), however, ranking the alternatives is more ambiguous. The reason is that in this theory, ways of behavior are not evaluated through the individual utility produced but through their ability to generate an outcome which assures survival. The degree to which a certain behavior improves survivability is called evolutionary fitness. The credo is that the fittest strategies will tend to dominate in the long-run as rivals die out sooner or later. Therefore, if individuals are in competition with each other, the fittest strategy must be established.

Figure 1 indicates that this strategy cannot be identified uniquely. Rather, the evolutionary fitness of both profiles depends on the precise payoff needed to survive and, thus, on competitive conditions. This argument can be illustrated formally as follows: With k being the threshold outcome needed to survive, the evolutionary fitness, F, of some behavior α, can be written as:

$$F_\alpha(k) = \int_{x=k}^{\infty} PDF_\alpha\,(x) \tag{1}$$

Based on this principle, some behavior α is fitter than any alternative behavior β if and only if α offers a higher probability to attain an outcome greater than k. Formally:

$$\alpha \gg \beta \leftrightarrow F_\alpha(k) > F_\beta(k) \tag{2}$$

where "≫" should be read as "dominates", in the sense of "fitter as".

For any k with $k < a$, it is easy to see that $\int_{-\infty}^{x=k} PDF_1\,(x) < \int_{-\infty}^{x=k} PDF_2\,(x)$ and, thus, $\int_{x=k}^{+\infty} PDF_1\,(x) > \int_{x=k}^{+\infty} PDF_2\,(x)$. In other words, whenever preventing relatively bad outcomes (equal or smaller than a) is sufficient for survival, profile 1 strictly dominates 2.

In contrast, for any $k > b$, it can be seen that $\int_{x=k}^{+\infty} PDF_1(x) < \int_{x=k}^{+\infty} PDF_2(x)$. Accordingly, if survival requires large outcomes, profile 2 provides the better fitness.

The considerations above are kept as simple as possible but convey an important message: A strategy which is worse than another with regards to its expected outcome but equipped with larger outcome variance may still be prevalent in a competitive environment if competitive conditions are appropriate. Proposition 1 takes this insight onto a more general level.

Proposition 1:

Assume two behaviors, 1 and 2, whose outcomes are distributed normally with means u_1 and u_2 and variances σ_1^2 and σ_2^2. Furthermore, assume that $u_1 > u_2$ with $\{u_1, u_2\} \in]-\infty; +\infty[$ and $\sigma_1^2 < \sigma_2^2$. Then, for any setting of $\{u_{1,}u_2, \sigma_1^2, \sigma_2^2\}$ complying with the above conditions, there is some threshold payoff k for which behavior 2 dominates 1 according to definition (2). (Proof in appendix)

Proposition 1 has a meaningful implication for the selection among agents. Why? Maximizing outcome expectation at a given outcome variance requires knowledge, skill, or other abilities. Portfolio theory, for example, teaches the theoretical knowledge to maximize expected return on investment at a given risk through intelligent composition of assets. To increase outcome variance at a given expectation, however, such abilities are not essential. Taking risks, respectively gambling, is sufficient. Against this background, proposition 1 can be read as follows. Under the assumption that undertaking risks increases the probability of attaining extreme outcomes, any less capable group can succeed in competition with a higher capable group if it undertakes enough risk and if the outcome needed to survive is sufficiently high. In respective scenarios, risk-seeking behavior per se provides evolutionary fitness.

The evolutionary model presented in the next section aims at sharpening our understanding about how such competitive scenarios may arise in practice, and how the outcome needed to survive can result endogenously from competitive conditions. The insights gained in this section will be helpful to interpret the simulation results obtained.

3 Example: An Abstract Model of the Competition among Fund Managers

This section highlights an evolutionary model of the professional competition among fund managers. This practical example is appropriate as it fulfills two important conditions: (i)

Agents compete with each other through the outcome generated by their behavior, and (ii) risk-preferences are a crucial determinant of this behavior. Section 3.1 introduces the model, Section 3.2 describes the setup of the simulation experiments, and Section 3.3 presents the simulation results.

3.1 The Model

The competition among fund managers has been sketched recently by N.N. Thaleb (2001). The author, himself a fund manager for several years, indicates that fluctuation in the profession is large. Professional status is highly dependent on the profitability of the managers' investments and changes quickly. In particular, unsuccessful managers are dismissed rapidly, no matter if their failing was due to chance or lack of skill. Empirical studies confirming and extending these insights include Chevalier and Ellison (1999a,b), Golec (1996), and Khorana (1996). Chevalier and Ellison (1999a) and Golec (1996), for instance, report that differences of the performance and the risk involved between mutual funds can be attributed to the behavior and different characteristics of the individual managers. Khorana (1996) shows that manager performance, which is either measured in terms of the adjusted asset growth rates or in terms of fund portfolio returns, is indeed used as selection criterion since "there is an inverse relation between the managerial performance and fund performance". Finally, Chevalier and Ellison (1999b) delivers evidence that managers react to the resulting competitive pressure by adjusting their investment behavior, and more specifically, their attitude towards risk. For example, young managers are found to hold more conservative portfolios since they are more likely to be replaced when performing badly.

In the following, a model which replicates the real competition in a stylized fashion will be introduced. As its principle, the approach rests on agent-based modeling. Agent-based modeling is the reproduction of complex systems through the formulation of specific assumptions about the behavior of agents and their interaction. The collective volumes by Rosser (2009) and Tesfatsion and Judd (2006) demonstrate the potential of this method for the analysis of social and financial systems. Note that our model is not meant to be a precise reproduction of reality but to uncover emergent phenomena on a general level and in a tractable framework. For a better overview, the framework will be described in three parts: (i) the investment logic, (ii) the selection mechanism, and (iii) the genetic algorithm, with (ii) and (iii) representing characteristic elements of an evolutionary model. [31]

[31] A Netlogo-version can be received by e-mailing to the author. The open-source simulator Netlogo is available here: http://ccl.northwestern.edu/netlogo/

(I) INVESTMENT LOGIC:

The investment logic can be summarized by the following rules:

(1) Each agent i disposes of some amount of capital at some period t, denoted by $C_{i,t}$. $C_{i,t}$ is invested into two classes of assets: a riskless and a risky one.

(2) Assets of the riskless class offer a constant, real return, μ_L. The real return produced by risky assets follows a normal distribution with mean μ_R and variance σ_R^2, with $\mu_R > \mu_L$, and $\sigma_R^2 > 0$.

(3) The share of capital invested in the risky asset by agent i is expressed by s_i. s_i is a mirror of i's degree of risk-aversion: A lower s_i, reflects greater risk-aversion, as i is willing to forego more payoff on average for the purpose of a lower likelihood of extremely bad payoffs.

(4) Furthermore, agents can undertake additional risk, denoted by δ. The additional risk of the portfolio of agent i, δ_i, increases the variance of the portfolio without improving the expected return.

(5) Portfolios pay-off in every period t, and the pay-off generated is reinvested instantly. Consequently, the evolution of capital results as:

$$C_{i,t+1} = (1 + g_{i,t})C_{i,t},\ with\ g_{i,t} \in N(\mu_i, \sigma_i^2)\ , \quad (3)$$

where $g_{i,t}$ stands for the real return of i's portfolio in period t; μ_i is the expected return and σ_i^2 the variance of i's portfolio. Returns $g_{i,t}$ are assumed to be independent between agents.

The investment logic defined above is fairly simple but allows a large range of portfolios. In accordance with portfolio theory, the portfolio of some agent i can be described by its expected payoff, μ_i, and the payoff variance, σ_i^2. In our model, both values are determined by the two attributes of the respective agents: the share of capital invested in the risky asset, s_i, and the amount of additional risk taken, δ_i. We get:

$$\mu_i = s_i * \mu_R + (1 - s_i)\mu_L \quad (4)$$

and

$$\sigma_i^2 = s_i * \sigma_R^2 + \delta_i \quad (5)$$

Figure 2 illustrates the resulting set of possible portfolios in the common form of a risk-return diagram (Brealey and Myers 2003).

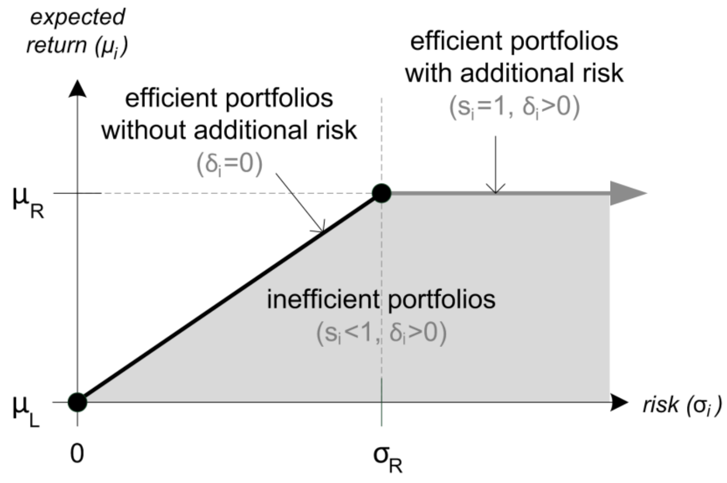

Figure 2: Risk-return diagram of portfolios possible.

The diagram shows that, depending on the choice of s_i and δ_i, efficient as well as inefficient portfolios may occur. If $\delta_i = 0$ (black line), an efficient portfolio results because, given the respective payoff variance, it is not possible to achieve a better return expectation. For any $\delta_i > 0$ and $s_i < 1$ (gray area), the portfolio is inefficient since a higher expected return could be attained at equal risk by increasing s_i. This is not possible if $\delta_i > 0$ and $s_i = 1$ (gray line); hence, the portfolio is efficient. In principle, portfolios can be any in the gray area and on its borders (including the infinite, omitted range following on the right which corresponds to a further rise of δ_i).

Let us conclude by a brief comment on the variable δ_i. Through δ_i, the model setup implies that the variance of the portfolio return can be raised arbitrarily. This may appear to be an unrealistic assumption. However, achieving greater outcome variance in reality requires little. Placing the raw investment payoff on bets with an expected return of zero is sufficient, technically. The analogue of the financial world would be investments in speculative assets with the chance for extreme returns but relatively poor expectation (e.g. so-called Junk Bonds). Choosing such assets, or respectively a positive value of δ_i, can be interpreted as risk-seeking behavior. On the other hand, if $\delta_i > 0$ implies an inefficient portfolio, a positive δ_i can be read as lack of skill: The agent could attain a better expectation at equal risk but she has simply not learned the appropriate investment behavior. In other words, we interpret “skill” as the ability to build an efficient portfolio.

(II) Selection Mechanism:

The selection mechanism, as one of the principal elements of an evolutionary model, is essential for the evolution of the population. For this purpose, the selection alternatives (here:

different investment behaviors represented by the agents using them) are evaluated by a defined criterion, setting them in competition with each other. The better an alternative fulfills the target, the higher the likelihood of spreading instead of dying out.
In the present model, selections are undertaken by an external entity, which can be interpreted as the employing company. The rules of selection are:

(6) In constant intervals of time, the worst agents are excluded. The length of this interval is specified by the parameter v. Another parameter, r, specifies the precise percentile of agents to be excluded.
(7) The criterion of selection is the return achieved by agents i in the v periods preceding to t, denoted by $g_{i,t,v}$. Due to (3), this return is mirrored by the relative change of individual investment capital. $g_{i,t,v}$ can thus be written as:

$$g_{i,t,v} = (C_{i,t} - C_{i,t-v})/C_{i,t-v} \tag{6}$$

With v and r, the selection mechanism described above has two parameters, where v represents the "exclusion interval" and r the "exclusion rate". Each parameter has a distinct function for the competition among agents. The exclusion rate has a direct effect on competitive pressure. The higher r is, the more agents are excluded, and the greater the outcome needed to survive. The exclusion interval, on the other hand, constitutes agents' "probation period". The higher v is, the more time agents have to produce investment returns.

Of course, we do not believe that promotions and exclusions in reality follow the rigorous mechanism described above. Instead, v and r should be regarded as a stylized representation of the probation time and the performance needed to be promoted. This design accounts for our general goal to keep the model simple and tractable.

(III) THE GENETIC ALGORITHM:

By specifying the set of agents to be excluded, the selection mechanism determines the outflow from the population. In contrast, the genetic algorithm relates to the inflow by establishing the character of agents entering the population.[32]

Genetic algorithms, originated by J.H. Holland (1975), are learning methods which mimic the biological process of evolution. A genetic algorithm creates "candidate solutions"

[32] It is also common to interpret the selection mechanism as a part of the genetic algorithm. From that point of view, (iii) is equivalent to the "reproduction mechanism". However, we do not adopt this view for the present model, because our selection mechanism could be implemented without genetic programming, and thus, does not contribute to the genetic feature of the model.

from a defined set of building blocks, which can be interpreted as genes. The construction of candidates is based on two genetic operators: crossover and mutation. Crossover is combining two candidate solutions, the “parents”, to create a new one. Then, some of the genes of the new code are modified slightly, which is denoted as mutation. Typically, the resulting candidate solutions are not preselected by a defined fitness criterion but prove their fitness in competition with each other.

The technique has considerable advantages. The modeler must not define an initial set of candidates to be evaluated but merely their building blocks. Therefore, less previous knowledge about possible solutions is required. Furthermore, the search space usually becomes extremely large. Thus, the solution finally found is likely to beat the best one in the limited set of alternatives the modeler would propose himself (with the restriction that the set of potential solutions is limited by construction rules and building blocks).

Due to these features, genetic algorithms have proven to be a successful tool in many economic models – Safarzyńska and van den Bergh (2010) review some of them with focus on the modeling techniques used. Goals of application are in particular the derivation of optimal rules of trading and investment, as conducted by Lensberg (1999), Lensberg and Schenk-Hoppe (2007), Letteau (1997), Neely et al. (1997) and Potvin et al. (2004). Hauser and Kaempff (2011) represent a recent contribution from the Journal of Evolutionary Economics. A study which is related to the present one quite closely is Letteau (1997). Like in the present study, Letteau’s agents build a portfolio by choosing the share of capital, s, to be invested in a risky asset; to find the optimal value, s^*, the genetic algorithm is used. However, in contrast to the present study, the focus is not on professional investors and their competition, but agents seek to maximize their own utility function. The latter follows the standard CARA design ($U(w) = -\exp(-\gamma * w)$), with γ being the risk-aversion coefficient and w the investment payoff), which excludes risk-seeking behavior ex ante. The goal of the study is to explore if evolution will lead to the optimal solution s^* – the one which generates the greatest utility on average. (Analytically, s^* is easy to derive: $s^* = (\mu_R - p_R)/\gamma\sigma_R^2$, with p_R being the price of the risky asset). The author finds that this result is actually reached if simulation time is long enough. For shorter horizons, however, the solutions tend to exceed s^*. The reason for the latter finding is quite interesting: In the short term, agents holding large shares of risky assets can be lucky and achieve great utility. This creates a bias towards greater solutions for s than s^*. The influence of chance tends to decrease if the period under observation is longer. In a different fashion, this phenomenon will also be observable in the present study.

The implementation of the genetic algorithm in our model is relatively easy because agents are characterized by two attributes only: the share of capital invested in the risky asset, s_i, and the amount of additional risk undertaken, δ_i. The algorithm can be outlined as follows:

(8) The excluded agents are replaced by "newcomers". The investment behavior of the newcomers is determined by a genetic algorithm.
(9) Each newcomer has two genetic parents, who are randomly chosen survivors of the present selection.
(10) Initially, each of the two attributes of the newcomer is adopted identically from a different parent. This leads to a temporary setting of attributes.
(11) The final setting is reached by a slight, random alteration of one randomly chosen attribute of the temporary setting.

In the algorithm described above, rule (10) reflects crossover, and (11) mutation. Together with (9), (10) guarantees that an investment behavior is more likely to spread, the more successful it has proven to be for the survival of competition. Rule (11) effects that virtually any investment behavior, that is, any combination of values of s_i and δ_i can emerge. In other words, any of the portfolios marked in figure 2 is actually possible. Regarding the world of fund managers, "crossover" stands for a combination of existing investment strategies, e.g. considering different rules for the selection of assets simultaneously. On the other hand, "mutation" refers to the invention of completely new selection rules.[33]

In the following, the evolutionary model is used to explore two principal research questions:

- Will evolutionary competition always lead to the prevalence of agents with efficient portfolios? Transferred to the model world: Will there be any agents with $\delta_i > 0$ and $s_i < 1$ at the simulation end?
- Which investment behavior is most successful in competition under different competitive conditions? Transferred to the model world: Which values of δ_i and s_i will have emerged under different settings of competition parameters, *v* and *r*?

To answer these questions, simulation experiments are conducted, whose setup will be described in the following section.

[33] Of course, the Darwinian approach of evolution described here is not an accurate representation of the evolution of strategies in reality. This is evident by the fact that fund managers do not use to have two fund manager parents. What is important for our purpose is that the algorithm is capable of uncovering the fittest behavior.

3.2 Simulation Setup

The model calibration consists in the setting of six parameters: the three asset parameters, μ_R, μ_L and σ_R^2; the two competition parameters, v and r; and the size of the population, N. According to rule (2) in Section 3.2, the asset parameters are subject to the restrictions $\mu_R > \mu_L$, and $\sigma_R^2 > 0$. Complying with these restrictions, we set $\mu_R = 3\%$, $\mu_L = 0\%$, and $\sigma_R = 5\%$. Judged by empirical data, this setting can be regarded as rather conservative. For example, in the time from 1950 to 2009, the inflation adjusted total return per year produced by US large company stocks (S&P 500) was 9.68% on average with a standard deviation of 17.40%.[34] Thus, the risky asset in our model still has a less risky profile than respective equivalents in practice.[35] The competition parameters, v and r, represent the independent variables. The exclusion interval v is incremented from 1 to 20 period(s), while the exclusion rate r is altered from 0.05 to 0.95 in steps of 0.05. Each combination of v and r signifies a different setup of competition, which gives a total of 380 scenarios to be simulated. Finally, N is set to 10,000. The large number of agents makes sure that the result of evolution can be reliably attributed to a systematic advantage of the respective investment behavior. The simulation runs terminate either if convergence is reached such that no significant change of agent attributes occurs anymore, or, in case of no convergence, if the path of evolution is evident (the latter will sometimes occur with regard to δ_i, which tends to rise continuously under specific competitive conditions). The initial setting of portfolio parameters is $s_i = \delta_i = 0.5, \forall i$, which corresponds to an inefficient portfolio. Agents thus have to learn an efficient investment behavior.

3.3 Results

Figure 3 depicts the results of the simulation experiments in an illustrative two-dimensional scheme. The upper lattice shows the share of capital invested in the risky asset, s_i, the bottom one the risk undertaken additionally, δ_i. Each square represents a particular setup of competition, as specified by the setting of exclusion interval v and exclusion rate r. Different gray-levels indicate the corresponding value of the dependent variables at the simulation end. The general rule is: the darker the square, the greater the value of the respective variable. In

[34] Data Sources: Ibbotson Associates (Nominal Total Return); Bureau of Labor Statistics (Inflation Rates).

[35] The reason not to adopt empirical data is that the empirical values vary largely relative to the time frame considered, as economic conditions are continuously changing. For example, between 1990 and 2009, the respective return is merely 2.79% with a variance of 19.52%. In conclusion, the empirical data are of little use for a reliable estimation of the risk-return profile of today's risky assets. Therefore we choose an artificial setting that appears to be realistic but conservative in so far as risky assets with comparable profiles are likely to exist in reality.

particular, white can be read as “0”. With regard to s_i, black stands for “1” (by definition s_i can never exceed 1). Regarding δ_i, black stands for extremely large values. The respective squares correspond to setups in which convergence is not reached. Hence, the values would continue to rise if the simulation went on. The lattices can be divided into five numbered areas. Each area represents a characteristic asset portfolio.

Area 1: In this area, the exclusion rate *r* is relatively low but the exclusion interval *v* is short, that is, exclusions take place relatively often. With these competitive conditions, evolution leads to the emergence of a portfolio which consists entirely of riskless assets ($s_i = 0$) and does not involve any additional risk ($\delta_i = 0$). As explained in Section 3.1, this configuration belongs to the class of efficient portfolios. Related to the level of agents, the respective portfolio corresponds to investors embodying maximum risk-aversion and skill, with the latter being interpreted as the ability to find an efficient composition of assets. The reason for the emergence of maximally conservative but efficient investment behavior lies in the specific requirements for survival. Due to the low exclusion rate, the prevention of extremely bad outcomes is sufficient for not being discarded. Furthermore, due to the short exclusion interval, random effects have hardly leveled out before returns are evaluated. As a result, undertaking risks is perilous, as risks raise the likelihood of attaining insufficient outcomes.

Area 2: The portfolios built in area 2 differ relative to area 1 in the parameter s_i. Investors continue to avoid additional risk ($\delta_i = 0$) but now spend a positive fraction of capital on the risky asset ($0 < s_i < 1$). Comparing the competitive conditions of area 1 and 2 reveals that this difference can be due to two reasons: a slight rise of the exclusion rate (i), or of the exclusion interval (ii). The causal paths from (i) and (ii) to the increase of s_i are quite distinct. By (i), the return needed to survive is enhanced. Pure risk prevention does not imply the best probability of achieving the respective outcomes because the amount of return expectation foregone becomes too great. Investing some capital in the risky asset increases the return expectation and, thus, improves survivability. Accordingly, a mixture of risky and riskless assets provides the best evolutionary fitness. By (ii), the same result is obtained through an extension of probation time. If the exclusion interval is raised, return expectation carries more weight because random effects tend to level out, leading to an evolutionary boost of agents with a positive fraction of risky assets. In other words, undertaking risk becomes less perilous for being eliminated if probation time increases. Note that the respective portfolios remain efficient and investors still behave in a risk-averse manner, however, to a smaller degree than in area 1.

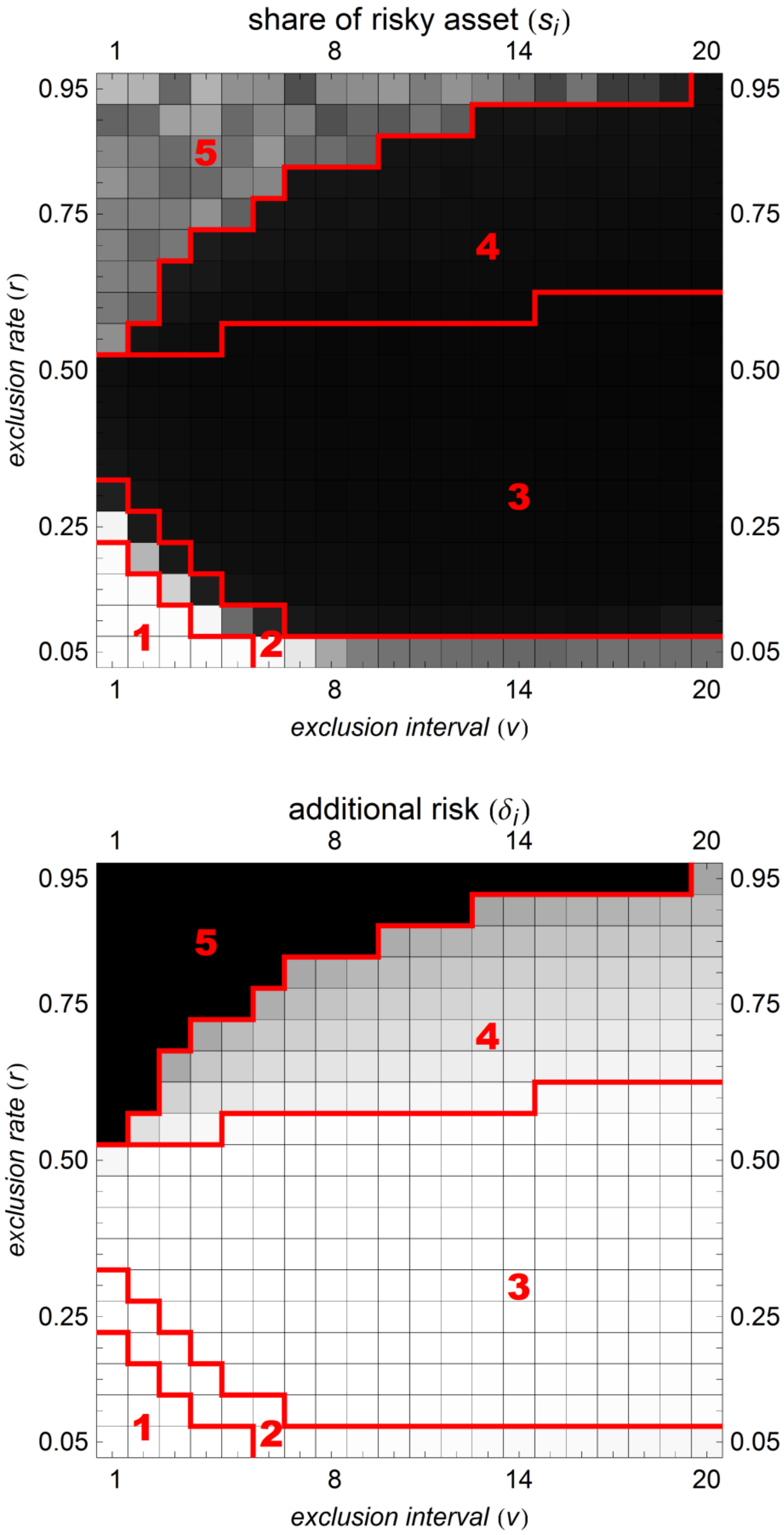

Figure 3: Values of portfolio parameters at simulation end for variable settings of competition parameters. Greater values indicated by darker gray tone.

Area 3: In area 3, the exclusion rate and the exclusion interval have increased further. As a result, the tendencies described above disembogue into an extreme. The fittest strategy is now simply to maximize return expectation as reflected by the fact that portfolios are composed entirely of risky assets ($s_i = 1$). This behavior reveals that risk-prevention does not provide any competitive advantage anymore. This result can be produced by a sufficient rise of any competition parameter; r or v. If r is raised sufficiently, any sacrifice of return expectation decreases evolutionary fitness because the relatively great outcomes needed are less likely to be attained. For a sufficient rise of v, any sacrifice of return expectation is harmful because return expectation tends to become the only criterion for survival.

The investment behavior in area 3 corresponds to risk-neutrality. Risk-neutrality implies that risks are not regarded as being a "value per se", which can be verified by the fact that agents do not undertake any risk if it does not enhance return expectation ($\delta_i = 0$). Apparently, undertaking additional risk deteriorates evolutionary fitness. The reason is that the exclusion rate is still low enough so that preventing extremely bad outcomes remains paramount towards seeking extremely good ones. Additional risk, hence, is not needed but rather destructive as it raises the probability of performing badly.

Area 4: Area 4 differs from area 3 in the very inclination of agents to undertake additional risk, which now converges at some positive value ($0 < \delta_i < +\infty$). This behavior is risk-seeking because agents accept risks even if the latter do not contribute to the maximization of return expectation. In other words, risk is regarded as a "value per se". The dominance of risk-seeking behavior is due to another rise of r, which has led to the transition of a critical level: 0.5 or 50%. To understand the phenomenon, assume that $v = 1$ and that the population consists of two groups: The first group obtains a sure periodical return of μ percent. The second group gets the same return μ but additionally plays a fair lottery which gives them a 50% chance for the return $\mu + \sigma$, respectively $\mu - \sigma$ in case of losing. It is easy to see that for both groups, the expected periodical return ($E[g_{i,t,1}]$) is equal to μ. If the population is sufficiently large, μ is also the median return; on average, half the population will achieve a return greater than μ whereas the other half falls below. However, if more than half of the population is excluded at selection periods ($r > 0.5$), the median return is not sufficient to proceed. This signifies a heavy competitive disadvantage for the first group because, in contrast to the second one, they never achieve a return greater than μ. The same occurs in the simulation. By choosing $\delta_i = 0$, agents accumulate probability mass of their return distribution near their return expectation. This is disadvantageous as the expected return does

not suffice to survive. Similar agents with $\delta_i > 0$ have greater fitness as more probability mass lies above the return needed. In conclusion, risk per se generates evolutionary fitness.
Still, the explanations above do not capture all mechanisms driving the simulation results. For example, they suggest that whenever $r > 0.5$, $\delta_i > 0$, which, as shown by figure 3, is not true. Another fact left to clarify is the convergence of δ_i on a specific value. Let us focus the latter phenomenon first. Basically, the convergence of δ_i on δ^* indicates that any agents with $\delta_i > \delta^*$ is less fit than an agent with $\delta_i = \delta^*$. The degree of risk which provides a competitive advantage, hence, is limited. To understand the cause, reconsider the second group mentioned above, which plays the lottery, and assume that $v = 2$, which implies the selection criterion to be $g_{i,t,2}$. Then, on average, half of the agents win in one period and lose in the other. The resulting return $g_{i,t,2}$ is $(1 + \mu + \sigma)(1 + \mu - \sigma) - 1$. It is easy to show that for any μ, this value decreases continuously with greater $|\sigma|$. In other words, agents who are moderately lucky achieve lower returns $g_{i,t,2}$ (and thus are less likely to survive) if the variance of their periodical returns is greater. The same happens in the model. Agents with $\delta_i > \delta^*$ require more luck than agents with $\delta_i = \delta^*$ to obtain the same return $g_{i,t,v}$. This effect is absent if $v = 1$ but increases for v being incremented above. As a result, agents chose lower values of δ_i , the greater v. This also explains why for some $r > 0.5$, $\delta_i = 0$. In the model, investing in the risky asset alone can generate the optimal return variance even without undertaking additional risk.

Area 5: The results in area 5 differ sharply from all previous ones in several aspects. Technically, the competitive conditions in this area are the only ones which do not disembogue in a convergence of portfolio parameters. In particular, the tendency of δ_i to rise does not settle down. Simultaneously, s_i fluctuates in a range below 1; an optimal weight of risky assets does not emerge. The chaotic pattern of different gray-levels confirms that the precise value of s_i at the simulation end is quite random. Because $s_i < 1$ and $\delta_i > 0$, the portfolios built are not efficient. In contrast to all previous ones, the competitive conditions in area 5 do not provoke the predominance of agents able or willing to choose an efficient composition of assets.
The peculiarity of these results shows that the competition in area 5 follows a logic which is very distinct. Apparently, skill is not an essential property to survive. Seeking risks, however, becomes vitally important. Any agent improves her evolutionary fitness by raising δ_i. These results are caused by the particular setting of competition parameters. Due to the great value of r and relatively low v, agents require large profits in a short span of time. To increase their

chance for such profits, they need to seek risks. However, investing in an equally risky manner than everyone else does not produce a competitive advantage. As a result, agents force each other into taking greater and greater risks in the attempt to excel their rivals. The counter effect described in area 4 – greater risks decreases the returns $g_{i,t,v}$ if being moderately lucky – is not relevant here because survival is only possible if very lucky.
Agents following these incentives build portfolios which enable them to attain huge profits. The actual return of these high-risk portfolios depends largely on chance. In contrast, differences in periodical return expectation, as determined by the setting of s_i, merely account for a minor part of actual returns. Hence, skill is of little importance. These findings mirror the insights from the theoretical analysis in chapter 2: Since the outcome needed to survive is relatively great, risk-seekers possess greater evolutionary fitness than risk-averters, even though the outcome expectation of risk-seekers is worse. As a result, the competition between agents leads to the predominance of risk-seekers who have been lucky, but who are not necessarily skilled.

Summary: The simulation results show that the fittest risk-preference is dependent significantly on competitive conditions. In this context, two competition parameters have proven to be decisive: the exclusion rate and the exclusion interval. The following relationships could be found: The greater the exclusion rate, that is, competitive pressure, the greater the advantage from risk-seeking behavior relative to risk prevention. Furthermore, the attractiveness of risky assets rises with greater exclusion interval, representing probation time, as chance tends to level out in the long run. Via these relationships, the setting of competition parameters can lead to various scenarios: risk-aversion, risk-neutrality, risk-seeking behavior and any risk preference in between can be the fittest behavior.

In addition, the simulation results reflect that the more risk involved by portfolios, the more actual returns are shaped by randomness and the less by the return expectation. As a result, skill is less important for survival, the more risks agents take. This logic can lead to an extreme scenario in which competition does not select the most skilled because skill is almost entirely blurred by chance. This scenario tends to arise if competitive pressure is intense and the great returns needed to survive must be produced in a short span of time.

Of course, the above insights raise the question about the actual competitive conditions in the fund manager profession. Analyzing empirical data from 1992 to 1994, Chevalier and Ellison (1999b) find that fear of being dismissed motivates young managers to choose low-risk portfolios. Against the background of our insights, this behavior indicates that competitive pressure was in the lower range in the time of data gathering. Future research should check if competitive conditions have changed today, which might contribute to the explanation of the attractiveness of high-risk investments.

3.4 Outlook

The analysis above has shown that certain competitive conditions lead to the emergence of risk-loving agents. It is an interesting question how this behavior of individuals affects the behavior of the respective macro system. Financial markets represent such a macro system whose dynamic is driven by individual traders and their interaction.

A model that touches this question is the Santa Fe Artificial Stock Market (SFI market) (summary by LeBaron et al. 1999). As in our study, agents in the SFI market can choose between a risky or riskless asset. Another common feature of the model framework is that the population of agents evolves via a genetic algorithm. The simulation experiments concentrate on two different settings of the learning rate which turns out to be a crucial parameter for the behavior of agents and for the dynamics of the market. A fast learning rate can be compared to a low exclusion interval (the parameter v in our model) because strategies have to prove their value in a short period of time. It is found that with a fast learning rate, agents tend to rely on technical instead of fundamental trading strategies. Technical strategies aim at returns beyond fundamental payoffs and can be compared with risk-seeking behavior. The interaction of these agents leads to a destabilization of the market in terms of greater excess returns and fatter tails of the return distribution.

In this fashion, the article of LeBaron (1999) gives an idea about the connection between competitive pressure, the behavior of agents, and market dynamics. Future work could concentrate on this connection in more detail. For example, it would be interesting to expand our model to include a financial market which is driven by the interaction of our agents, while feeding back to the profit of their strategies. This might produce a broader picture of the mechanisms driving real world scenarios.

4. CONCLUSION

The present article explores the relationship between various competitive conditions and the evolutionary fitness of different risk preferences. The analysis is conducted theoretically as well as by an evolutionary multi-agent model that reproduces an exemplary empirical case in a stylized fashion: the competition among fund managers. This case reflects the problem very well because the risk preference of managers is a central determinant for the composition of their asset portfolio whose return managers compete about. To simulate how fund managers develop their strategies, a genetic algorithm is applied, which ensures that virtually any combination of portfolio parameters can emerge as the fittest.

On the whole, we observe that competitive environments have great influence on risk preferences and investment behavior. Hereby, two variables play a central role. On the one hand, there is the exclusion rate. A high exclusion rate means high competitive pressure and creates the need for large outcomes. This makes risk-seeking behavior attractive because the probability of high outcomes is increased. On the other hand, the time conceded to agents to attain the outcomes is crucial as random effects tend to even out in the long-run. All in all, these mechanisms can cause the emergence of risk-aversion in any degree but also risk-seeking behavior.

The latter fact gives raise to warnings. Under competitive conditions that favor risk-seeking behavior, the importance of skill (the ability to build an efficient portfolio) decreases because actual outcomes are determined mostly by chance. In the extreme case, survivors are not the most skilled but simply the luckiest risk-seekers. The simulation model reflects this phenomenon by showing that, in the respective competitive conditions, agents with inefficient portfolios can survive, provided that they choose high risk investments. Such scenarios are dangerous on any economic level, not only with reference to the competition between fund managers, because of two reasons. First, because the predominance of the most capable is undermined, and second, because the risky behavior of agents implies unforeseeable outcomes which run counter to economic stability. An example is the competition between banks. Banks that are in heavy competition with each other have greater incentives to invest in a risk-seeking way. As a consequence, they become more vulnerable to economic crises so that the economic breakdown is reinforced.

To prevent these scenarios, our study yields two recommendations. First, competitive pressure must be held strictly below some critical level from which risks per se generate a competitive advantage. In the model, this is achieved by setting the exclusion rate to a low or moderate level. Second, probation time should be sufficiently long such that skill instead of chance shapes individual outcomes.

By showing that competitive conditions can lead to the emergence of risk-aversion or risk-taking behavior in various degrees, our model combines insight from previous research. Szpiro (1997), for example, uses a genetic algorithm to explain risk-aversion. On the other hand, Rubin and Paul II (1979), Robson (1992, 1996) and other contributions mentioned before, focus on risk-taking behavior. A nice feature of our model might be its ability to reproduce both scenarios in a relatively simple and illustrative agent-based framework that demonstrates the importance of competitive conditions.

We believe that several mechanisms that drive the result of our simulations can be condensed algebraically. This is going to be a focal point for future research.

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APPENDIX

Proof of Proposition 1:

To prove proposition 1, we have to show that the PDF of profile 2 is strictly greater than the one of profile 1 for $x \to +\infty$. Since by assumption both profiles represent normal distributions, the inequality to prove can be expressed as follows:

$$\lim_{x\to+\infty}\left(\frac{1}{\sqrt{2\pi}\sigma_2}e^{-\frac{(x+\mu_2)^2}{2\sigma_2^2}} > \frac{1}{\sqrt{2\pi}\sigma_1}e^{-\frac{(x+\mu_1)^2}{2\sigma_1^2}}\right)$$

s.c.:

(i) $\mu_2 = \mu_1 + \Delta_\mu$ with $\Delta_\mu \in\ ]-\infty;+\infty[$

(ii) $\sigma_2 = \sigma_1 + \Delta_\sigma$ with $\Delta_\sigma > 0$ and $\neg(\sigma_1 \to 0)$

To start, replace μ_2 and σ_2 by its correspondences. Logarithmize, and simplify the result. This gives:

$$\lim_{x\to+\infty}\left(\frac{(x-\mu_1+\Delta_\mu)^2}{2\sigma_1^2+4\sigma_1\Delta_\sigma+2\Delta_\sigma^2} < \mathrm{Z}\right) \qquad \text{with } \mathrm{Z} = \frac{(x-\mu_1)^2}{2\sigma_1^2} + \mathrm{Log}[\sigma_1] - \mathrm{Log}[\sigma_1 + \Delta_\mu].$$

Next apply the equivalence $\frac{a}{b+c} = \frac{a}{b} - \frac{ac}{b(b+c)}$ setting $a = (x - \mu_1 + \Delta_\mu)^2$, $b = 2\sigma_1^2$, and $c = 4\sigma_1\Delta_\sigma + 2\Delta_\sigma^2$. This gives:

$$\lim_{x\to+\infty}\left(\frac{a}{b} - \frac{ac}{b(b+c)} < \mathrm{Z}\right)$$

Expanding a in the first term and rearranging the result leads to:

$$\lim_{x\to+\infty}\left(\frac{(x-\mu_1)^2}{b} + \frac{\Delta_\mu^2 - 2\Delta_\mu\mu_1 + 2\Delta_\mu x}{2\sigma_1^2} - \frac{ac}{b(b+c)} < \mathrm{Z}\right)$$

Expanding Z and subtracting $\frac{(x-\mu_1)^2}{b}$ from both sides finally yields:

$$\frac{\Delta_\mu^2 - 2\Delta_\mu\mu_1 + 2\Delta_\mu x}{2\sigma_1^2} - \frac{ac}{b(b+c)} < \mathrm{Log}[\sigma_1] - \mathrm{Log}[\sigma_1 + \Delta_\sigma]$$

It can been seen that the instance of x with the highest power is included in a with x^2. The limit of the left side as x approaches $+\infty$ is thus determined by the term $-\frac{ac}{b(b+c)}$ whose limit is $-\infty$. Since due to (ii), the limit of the right side is greater than $-\infty$, the inequality is true.

q.e.d.

4

Removing Systematic Patterns in Returns in a Financial Market Model by Artificially Intelligent Traders

Björn-Christopher Witte

Abstract: The unpredictabiliy of returns counts as a stylized fact of financial markets. To reproduce this fact, modellers usually implement noise terms − a method with several downsides. Above all, systematic patterns are not eliminated but merely blurred. The present article introduces a model in which systematic patterns are removed endogenously. This is achieved in a reality-oriented way: Intelligent traders are able to identify patterns and exploit them. To identify and predict patterns, a very simple artificial neural network is used. As neural network mimic the cognitive processes of the human brain, this method might be regarded as a quite accurate way of how traders identify patterns and forecast prices in reality. The simulation experiments show that the artifical traders exploit patterns effectively and thereby remove them which ultimately leads to the unpredictability of prices. Further results relate to the influence of pattern exploiters on market efficiency.

Keywords: financial markets; autocorrelations; artificial intelligence; agent-based modeling

JEL classification: C45; G14; G17

1. Problem Setting

As one of their most essential statistical properties, price returns on financial markets are free from significant autocorrelations. Being a stronger proposition, advocates of market efficiency believe that financial markets are virtually unpredictable (see Fama, 1965, in this context). Whereas the absence of autocorrelations (AA) is easy to show econometrically, the Absence of Systematic Patterns in price dynamics (ASP) is harder if not impossible to verify, as the number of potential patterns is infinite and patterns can be highly complex. Technical trading takes the existence of such patterns as its central credo, and empirical studies provide some evidence that some systematic patterns do exist, e.g. the so-called January Effect (Thaler, 1987). Nevertheless, AA and ASP remain accurate outlines of market behavior.

The general fulfillment of AA and ASP is a product of the profit-seeking behavior of traders. At the moment traders identify or believe that they have identified a systematic pattern in prices, they trade on it and thereby exploit it, which ultimately leads to the extinction of the particular pattern.[36]

Financial market models (surveys by Hommes, 2006, and LeBaron, 2006) seek to imitate the statistical properties of real markets. AA and ASP, therefore, constitute important criteria to evaluate the accuracy of the behavior of these models. To test econometrically if prices evolve more or less unpredictably, modelers usually limit themselves to the replication of AA. AA is a necessary condition for ASP but not a sufficient one as systematic patterns might be too complex to be mirrored in significant autocorrelations.

Table 1 provides an overview of selected financial market models with regard to the particular method used to reproduce AA. The table is based on the survey by Chen et al. (2011). The authors review 50 financial market models, classify them according to their origin and design, and report the particular stylized facts explained. The 27 models which, according to the authors, "explain" the absence of autocorrelations have been examined in more detail.

[36] We admit that this logic is idealized. Regularities could be extremely complex such that traders do not recognize them, or some traders do recognize them but their trading capital could be too low to exploit the pattern entirely (analogue to the well-known "limits of arbitrage" by Shleifer,1997). Further, the argument is not valid for mid-term or long-term patterns. For example, financial dynamics appear to oscillate in the long term due to business cycles (Greenwald and Stiglitz, 1993).

Nr.	Article	Origin	Method for AA replication	Comment
			2 Type Design	
1	Alfarano, Lux, and Wagner (2005)	IAH	Noise trader	AA not perfect
2	Chiarella, He and Hommes (2006)	ABS	Random demand term in price adaption	
3	De Grauwe and Grimaldi (2005)	ABS	Exogenous noise: “Forecast errors of chartists and fundamentalists”	AA not shown
4	Gaunersdorfer and Hommes (2007)	ABS	Random term in price adaption. "Noise Trader”	
5	Gilli and Winker (2003)	ANT	Random price shocks, noise in majority assessment	
6	He and Li (2007)	ABS	Random term in price adaption. "Noise Trader, unexpected market news"	
7	Hommes (2002)	ABS	Dividend noise, model approximation noise	
8	Kirman and Teyssiere (2002)	ANT	Random exchange rate, random interest rate.	
9	Li and Rosser (2004)	ABS	None	AA not perfect
10	Manzan and Westerhoff (2005)	ABS	Demand entirely determined by randomly arriving news	
11	Winker and Gilli (2001)	ANT	Random demand term	
			3 Type Design	
12	Lux and Marchesi (2000)	IAH	Transition probabilities	AA not perfect
13	Parke and Waters (2007)	ABS	Martingale news, martingale dividends	
			Many-Type Design	
14	Challet and Galla (2005)	MG	Probabilistic trading decision	AA for some setups only
15	Cross, et al. (2007)	MG	Random term in price adaption representing "exogenous information stream"	
16	Dicks and van der Weide (2005)	ABS	Random news affecting traders expectation	Random Walk of Prices
17	Ferreira, et al. (2005)	MG	Pattern exploitation?	
18	Ghoulmie, Cont and Nadal (2005)	TM	Random trading signal	
19	Iori (2002)	IM	Random trading signal (individual)	
20	Pollard (2006)	TM	Gaussian trading signal (“morning news”)	AA not shown
21	Sallans, et al. (2003)	ABS	Random actions	AA not perfect
22	Shimokawa, Suzuki and Misawa (2007)	PT	Noise trader, Gaussian private signals for price prediction	AA not shown
			Autonomous Agent	
23	Arifovic and Gencay (2000)	SFI		No AA
24	LeBaron, Arthur and Palmer (1999)	SFI	Stochastic dividend process	AA not shown
25	Martinez-Jaramillo and Tsang (2007)	SFI	Pure noise traders	AA not perfect
26	Reimann and Tupak (2007)	SFI	random dividend process	
27	Tay and Lin (2001)	SFI	Stochastic dividend process, Random expectations of prices and dividends	

Table 1: Financial Market models listed in Chen (2011) method used to reproduce the absence of autocorrelations in returns (AA). Acronyms: ANT: Ant; ABS: Agent-based modeling; IAH: Interactive agent hypothesis; IM: Ising model; MG: Minority games; PT: Prospect-theory-based; SFI: Santa Fe artificial stock market; TM: Threshold model.

The table illustrates that to reproduce AA, modelers commonly use stochastic model components, and this applies for every model design and origin.[37] In some models (e.g. table entries 2, 4, 6 and 11), such noise terms are contained directly in the mechanism of price formation. Others chose more elegant, indirect solutions by implementing random terms into the behavior of agents (12, 21) or into the components agents react to, which can be news (10, 13, 20), trading signals (18, 19, 22) or dividends (13, 26, 27). A popular argument to implement stochastic components refers to the behavior of so-called "noise traders" (1, 4, 6, 25). According to Black (1986), noise traders "trade on noise as if it were information". As the particular behavior of noise traders does not follow a uniform logic, it can be nicely approximated stochastically.

The use of stochastic components is a viable and effective way to replicate AA. It is effective since by adding a sufficient amount of noise, the systematic behavioral patterns the deterministic model framework would generate can be blurred and prices evolve largely unpredictably. Nevertheless, the method is not free from considerable downsides. First, the amount of noise needed to eliminate detectable patterns can be very large, such that merely a small part of the movements of prices remains attributable to explicit model components. In general, the amount of noise needed declines with the structural complexity of the model as the interaction of deterministic mechanisms can lead to richer behavior. Greater model complexity, however, deteriorates the model's tractability. Second, if random demand terms are chosen, a significant proportion of the total demand originates model-exogenously. It would be more desirable to model the sources of this demand explicitly, and thereby to improve the subjective completeness of the model. Third, the greater the share of total demand which arises randomly, the worse prices react to shifts of fundamentals. As a realistic behavior, we would expect that fundamental news is reflected more or less in changes of prices, at least when the news is considerable. Fourth, through stochastic components, systematic patterns are never removed in a strict sense but merely blurred. A mechanism causing the elimination of patterns endogenously is absent. Therefore, a genuine explanation for the absence of systematic patterns is not given.

The present article presents a model in which systematic patterns are removed endogenously, and without exogenous noise (apart from fundamental news) being added. The

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[37] Of course, the reproduction of AA is not the only purpose of using stochastic components. Producing volatility clustering or simply capturing effects which should not be modeled explicitly are examples for other functions. The modification of the grand-canonical minority game (e.g. Slanina et al. 1999) in table entry 17 constitutes an exception, as the authors attribute the AA-property to the fact that "speculators are exploring all available information". Unfortunately this feature is not presented in detail.

method is inspired by reality as it assumes traders are able to detect patterns in price dynamics and to exploit them. To detect and predict patterns, a linear regression model is used. The linear regression model can be interpreted as the simplest form of an Artificial Neuronal Network (ANN). ANNs mimic the information processing of the human brain technically and thus represent a relatively accurate way to model the perception of financial traders. As a second contribution, the simulations provide insights into the effect of pattern exploitation on market efficiency. It is shown that exploiters enforce the tendency of prices to reflect changes of value. On the other hand, the discrepancy between prices and value can rise.

The remainder of this article is organized as follows. Treating methodical issues, Section 2 illustrates theoretically how systematic patterns in prices can be removed endogenously. Section 3 deals with the application. At first, it introduces a simple model in which systematic patterns are recognized by traders and exploited. Then, the dynamic features of the model are illustrated while varying the impact of pattern exploiters. Section 4 summarizes the insights gained and highlights needs for future research.

2. Method: Endogenous Eliminating of Systematic Patterns

The endogenous elimination of systematic patterns embraces three components: (i) traders able to identify systematic patterns and to trade on them; (ii) a technique for the identification of these patterns; (iii) specific model features facilitating the effective implementation of (i) and (ii). In the following, the three components will be explained in the given order.

2.1 The Basic Idea

Consider an arbitrary asset market in which prices are formed in discrete steps of time. In such a framework, the price in time *t*, P_t, necessarily results from a set of information given at *t*. Let Φ_t denote this information set. Fundamental trading (Greenwald et al., 2001, Damodaran, 2002) rests on the belief that Φ_t includes fundamental information − the price of some asset is not completely independent from its fundamental value, F_t. Consequently, fundamental traders seek to identify F_t and to exploit mispricing. In contrast, technical trading (Murphy 1999, Pring 2002) assumes that Φ_t also includes past prices, $(P_{t-1}, P_{t-2},\ldots,P_{t-n})$. If the price in *t* is indeed influenced by the evolution of prices in the past, systematic patterns in prices exist. These basic insights can be formalized as follows.

$$P_t = g_t[\Phi_t], \qquad \Phi_t = [F_t, P_{t-1}, P_{t-2}, \ldots, P_{t-n}], \tag{1}$$

where g_t is a deterministic or stochastic function of arbitrary complexity describing the behavior of prices at time t. Note that (1) does not state that prices are necessarily influenced by their history nor by value (the respective coefficients in g_t could equal zero) but merely that these are possible determinants for prices.

Financial trading implies the formation of expectations about prices, where $E_t^i[P_{t+\Delta}]$ should denote the price of time $t+\Delta$ ($\Delta > 0$) expected by trader or trader group i at t. The expectation of a financial speculator is a central determinant for her[38] demand of assets. Taking this into account, in many financial market models, the formulation of the net demand is based on the following principle:

$$D_t^i = \alpha^i \left(\left(E_t^i[P_{t+1}] | \Phi_t^i \right) - P_t \right), \tag{2}$$

with

$$E_t^i[P_{t+1}] | \Phi_t^i = h_t^i(\Phi_t^i), \tag{3}$$

where α^i is a constant parameter, and Φ_t^i is a set of fundamental and/or technical information available in t and considered by i for the formation of expectations. The equation stipulates that traders buy (/sell) if the price they would pay (/receive) is below (/above) their expectation of the price in the next period, and their net demand rises with the difference between their expectation and the transaction price. α^i can be interpreted as i's reaction intensity as it regulates the net demand for a given value of $\left(E_t^i[P_{t+1}] - P_t\right)$. h_t^i is an arbitrary deterministic or stochastic expectation function. Popular examples are $h_t^F(P_t, F_t) := P_t + \delta^F(F_t - P_t)$ or $h_t^C(P_t, P_{t-1}) := P_t + \delta^C(P_t - P_{t-1})$, with δ^F and δ^C being positive parameters. h_t^F represents a stylized description of the philosophy of fundamentalists, who expect prices to return to value to some degree. h_t^C expresses the trend extrapolation by technical traders.

Deterministic features of the rules of trading, as the ones above, are the origin of systematic patterns in prices. For example, the behavior of technical traders with expectation function h_t^C induces a piece of positive feedback into the dynamics of prices. However, any mechanism which would work against these patterns is absent in the above framework.

Before an endogenous mechanism to remove systematic patterns is developed, it is helpful to recall the mechanism of how patterns may be removed in real markets. This mechanism involves three necessary steps:

[38] For the sake of inclusive language, the author will use the feminine pronouns to represent individual actions.

I. Pattern recognition: Traders recognize systematic pattern in price dynamics.
II. Pattern exploitation: Traders seek to take profits by trading on the patterns identified.
III. Pattern reduction: The exploitation of a pattern reduces its appearance and ultimately removes it.

A model in which all traders follow the rules h_t^F or h_t^C, or similar static rules, has problems fulfilling the very first necessary step (I): Traders do not recognize systematic patterns but stick to a constant trading behavior. The fulfillment of (I) requires that some traders seek to estimate the function $g_t(\Phi_t)$, which describes the actual behavior of prices. The index *X* should denote these "pattern exploiters". Their expectation formation can be written as:

$$E_t^X[P_{t+1}]|\Phi_t^X = \widehat{g_{t+1}}_t^X(\Phi_t^X), \tag{4}$$

where $\widehat{g_{t+1}}_t^X$ stands for the estimation of g_{t+1} (the function giving the price P_{t+1}) by exploiters in *t*. A trader forming his expectation according to (4) and formulating his demand according to (1), buys (/sells) for each price P_t for which she predicts a rise (/fall) of prices from *t* to *t+1*. This behavior is perfectly profit-oriented as the price change from *t* to *t+1* (i.e. the return $P_{t+1} - P_t$) determinates the immediate profit of the trader. The trading behavior specified by (1) and (2), hence, have satisfies step (II), as patterns are exploited.

Whether the exploitation of the identified pattern reduces the pattern identified or not, such that step (III) is fulfilled, depends on the mechanism of price adaption. Financial market models often use a stylized market maker as proposed by Farmer & Joshi 2002. The marker maker acts as an intermediary between supply and demand which reacts to the amount of excess demand in the market through the adjustments of prices. This behavior can be formalized as: $P_{t+1} = P_t + \alpha^M D_t$, where D_t represents the excess demand in the market at time *t* and α^M is a positive reaction coefficient. If the marker maker approach is chosen, step (III) can be violated. The reason is that prices do not necessarily reflect the expectation of traders, but the market maker herself can create systematic patterns in prices. For example, if the value of α^M is too high, the market maker overacts, and prices tend to fluctuate around the equilibrium price. The problem is prevented if equilibrium prices are computed directly. The respective formalization is:

$$P_t = P_t|(D_t(P_t) = 0). \tag{5}$$

To prove that in the market described, regularities can be removed endogenously, we formulate the following proposition:

Proposition 1:

If the following conditions are fulfilled, prices will evolve completely unpredictably: (i) every trader behaves according to equation (2) and (4); (ii) traders are omniscient – they know the function g_t and all relevant information contained in Φ_t in all t; (iii) prices result according to (5).

Proof:

Condition (ii) implies that $E_t^i[P_{t+1}] = E_t^j[P_{t+1}] = E_t[P_{t+1}]\ \forall i, j$ (If traders are omniscient, they will arrive at the same price expectation, $E_t[P_{t+1}]$). Using this equality, the total demand in the market, D_t, is given by a reformulation of eq. (2):

$$D_t = N * \alpha(E_t[P_{t+1}](\Phi_t') - P_t), \tag{6}$$

where N is the number of traders. Inserting (6) into (5) yields for the equilibrium price $P_t = P_t | \mathrm{N} * \alpha\big(E_t[P_{t+1}](\Phi_t^i) - P_t\big) = 0$. Since $N, \alpha > 0$, the only solution of latter equivalence is the price for which $(E_t[P_{t+1}](\Phi_t^i) - P_t) = 0$. Hence,

$$P_t = E_t[P_{t+1}](\Phi_t^i)\ \forall t. \tag{7}$$

In other words, under conditions (i – iii), at each time *t* the price P_t will be such that traders neither expect a rise nor a fall of prices in the next period, as P_t already reflects all information that traders believe to be relevant. Therefore, any non-zero return $r_{t+1} = P_{t+1} - P_t$ can only be due to information which traders did not consider in *t*. From the perspective of traders, the returns r_t are thus unpredictable for all *t*. Note that (7) alone does not imply prices are free from any systematic patterns but only from those patterns which traders have recognized. The absence of any pattern is dependent on the omniscience of traders as proposed by condition (ii). Omniscient traders know g_t and Φ_t by definition. Hence, any divergence of $P_t = E_t[P_{t+1}](\Phi_t) = g_t(\Phi_t)$ from $P_{t+1} = g_{t+1}(\Phi_{t+1})$ can only be due to true news – exogenous events that could not be known nor be expected in *t*. It is easy to see that such news can either be equal in a change of g_t or Φ_t from *t* to *t+1*. A change of g_t can be due to an alteration of the market structure (e.g. a new mechanism of price setting) or traders' behavior. A change of Φ_t, on the other hand, can only be caused by a shift of the fundamental value F_t from *t* to *t+1*, as all other information included in $\Phi_{t+1} = [F_{t+1}, P_t, P_{t-1}, \dots P_{t-n-1}]$ are already known to omniscient traders in *t* (including the price P_t, which, according to (1), is equal to $g_t(\Phi_t)$). As true news, such as new fundamental information, is by definition unsystematic and unpredictable, every price change from *t* to *t+1* will be unpredictable, too.

Proposition 1 describes an extreme, theoretical scenario, and aims at demonstrating that under specific conditions, any systematic pattern will be eliminated. The scenario is extreme and theoretical as it assumes the absence of any information deficit and perfectly rational behavior for all traders.[39] Of course, in reality – as well as in the agent-based model presented later – these conditions are not fulfilled, such that some systematic patterns might occur at least temporarily – think of a sequence of positive returns during a speculative rally, for example. However, the consideration above can be used to derive the determinants for the degree to which systematic patterns are actually removed. The first determinant is the relative trading power of pattern exploiters. Only if their trading power is sufficiently great will prices indeed fully reflect their expectation such that eq. (7) is fulfilled. A violation of this condition can be read analogously to the “limits of arbitrage” (Shleifer, 1997); Exploiters identify regularities in the evolution of prices but cannot exploit them entirely because their investment capital is too small. The second determinant is the knowledge of these traders. In principle, any pattern which is not identified correctly will not be exploited and, thus, can persist, although exploiters’ trading power might be great. If traders miss existent patterns or misinterpret them, their trading activity moves prices towards some value P_t for which under c.p. assumptions $P_{t+1} \neq P_t$. Hence, the following price change is not completely unforeseeable, although eq. (7) might be true. In the ideal case, exploiters have perfect knowledge about g_t and Φ_t at all *t*. In sum, the degree to which autocorrelations will be removed tends to be greater, the greater the trading power of pattern exploiters and the better their ability of pattern perception.

2.2 Techniques for Pattern Recognition and Price Prediction.

Eq. (1) has stated that the price in t is determined by $P_t = g_t[\Phi_t]$. The identification of patterns implies forming an estimation about g_t, denoted $\widehat{g_t}$. This estimation is then fundamental for price prediction. In this section, we briefly discuss three modeling alternatives to obtain $\widehat{g_t}$, including their pros and cons. Beside a) perfect knowledge, these alternatives are b) regression and c) artificial neuronal networks, where the latter two approximate g_t through price history.

[39] Still, the assumptions made are not unusual in economic theory, particularly in studies dealing with market efficiency. Fama (1965), for example, writes: An "efficient" market is defined as a market where there are large numbers of rational, profit-maximizers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants.” Having made this definition, Fama argues that under similar assumption, the activity of “intelligent” traders cause prices to follow a random walk, which is free from any systematic patterns. Unfortunately, Fama does not derive this point from a formal proof but from a verbal argument.

a) Perfect knowledge

Perfect knowledge of traders was occasionally assumed in Section 2.1. It implies that $\widehat{g_t} = g_t, \forall t$. As its greatest advantage, the method is the most effective one for the endogenous removal of systematic patterns, as any existent pattern will be exploited. Further, model complexity increases little, as no mechanism of pattern detection has to be implemented. On the other hand, perfect knowledge is not a realistic assumption for financial traders. Moreover, g_t can be very complex, because the behavior of pattern exploiters re-affects the law of motion, which in turn affects the behavior of exploiters. Solving such recursive problems can be intricate and identifying the true function g_t may be hardly possible.

b) Regression

If perfect knowledge is not given, traders have to identify regularities in prices from price history. The simplest method to do this is regression. As the first step, regression implies devising a reasonable regression model, which is a hypothetical relationship between the price P_t, representing the dependent variable, and the independent variables potentially determining P_t. For instance, agents could believe that prices P_t are possibly influenced by the present fundamental value F_t as well as by the prices in the two periods preceding, P_{t-1} and P_{t-2}, and that the relationship is linear. A corresponding generic form of $\widehat{g_t}$ is:

$$\widehat{g_t}(F_t, P_{t-1}, P_{t-2}) := P_t = \beta_1 F_t + \beta_2 P_{t-1} + \beta_3 P_{t-2} \tag{8}$$

(In the model introduced in Section 3, pattern exploiters will be realized by the very model above.) The second step consists of the estimation of the regression coefficients β_1 to β_n. To this purpose, agents use a defined frame of historical data, e.g. the last *N* periods, and set the regression coefficients such that a certain error criterion, e.g. the mean square error (here: $\sum_{k=t-N}^{-1}(E_k[P_k] - P_k)^2 / N$), is minimized for the time frame considered. For an advanced regression approach for stock market prediction, see Yang et al. 2002.

Choosing regression techniques for pattern detection is attractive as the method is relatively simple to implement and easy to understand. Nevertheless, by linear regression, autocorrelations in returns can be identified exhaustively. Hence, the method effectively contributes to the fulfillment of the stylized fact of no correlations in raw returns. However, the complexity of the regularities learnable is limited by the regression model. For instance, if the regression model is linear, traders cannot identify non-linear regularities and so their predictions will imply considerable systematic errors. Thus, not all complex patterns will be exploited and removed. If pattern complexity is greater, a regression model of at least equal complexity is required. The design of such models implies many degrees of freedom. Simply choosing the correct model (if ascertainable) implies that traders have profound previous knowledge, which might be an unrealistic assumption.

c) Artificial Neural Networks (ANNs).

ANNs (see Basheer and Hajmeer, 2000 for an introduction) may be regarded as the most sophisticated method of establishing $\widehat{g_t}$. ANNs are inspired by the human brain, which consists of complex webs of densely interconnected neurons. When the aggregate input of a neuron exceeds a certain threshold, the cell "fires" and activates other linked neurons if their stimulation is sufficient. Invented by psychologist Frank Rosenblatt in 1958, ANNs replicate the biological process numerically. Here, neurons are represented by artificial units organized in layers. The first layer is the input layer whose units each represent a sensor for the value of one independent variable (here: $\Phi_{\mathrm{t}} = [F_t, P_{t-1}, P_{t-2}, \dots P_{t-n}]$). The last layer is the output layer. The output unit yields the result, that is, the value of the dependent variable (here: P_t, respectively $E_t[P_{t+1}]$). Between input and output layer, several hidden layers can be implemented. Units in the hidden and output layers each represent functions. (Often sigmoid functions are used.) The input of each of these functions is the sum of the outputs of the units in the upstream layer with each output multiplied by a weight factor. Through the respective setting of these weight factors, the ANN can represent a variety of relationships between dependent and independent variables. The step of training aims at "teaching" the ANN the relationships existent in the particular case of application. The so-called Backpropagation algorithm is common for this purpose. The algorithm takes the network output and compares it to the target value of a set of training examples. The discrepancy is used as an indicator for how to adapt the weights within the network. Backpropagation denotes the successive retracing of the estimation error from the output unit to earlier units to correct their weight factors.

In general, the complexity of the function learnable by the ANN rises with the number of hidden layers and the number of units in these layers. An ANN which does not contain any hidden layers is equivalent to a linear regression model as it can only represent linear functions. The weights of such an ANN correspond to the regression coefficients *ß* and training the ANN will lead to the solution that minimizes a defined error criterion. The regression model specified by eq. (8) can thus be realized by an ANN. Interpreted that way, (8) can be regarded as quite an accurate reproduction of the cognition of relatively simple-minded but still intelligent traders.

To sum up, ANNs provide two considerable advantages: First, ANNs are capable of learning regularities of arbitrary complexity, provided that the number of hidden layers and units is great enough. Hence, by using ANNs, virtually any pattern can be eliminated, theoretically. The elimination of complex patterns is even possible by an ANN with a tractable structure. Cybenko (1988), for example, proves that any continuous and multivariate function can be approximated with an error approaching zero by a feed-forward network with only one hidden layer. Due to their ability to detect complex patterns, ANNs are a popular tool for financial forecasting (books on this topic were authored by Azoff, E.M. (1994) and Gately, E.J. (1996). For recent research see Majhi et al. 2009, or Nair et al. 2011). Second, ANNs are a very accurate way of modeling the perception of financial traders, because the principle derives from the workings of the human brain. Regarding this, financial market models using ANN-traders are still relatively scarce (examples include Beltratti, & Margarita 1992, Belratti et al. 1996, and Hommes 2001).

The scarcity of financial market models based on ANNs may be due to three reasons. First, although the ANN per se can be created quickly, using it in a reasonable way is an intricate endeavor. In particular, the configuration of the ANN involves many degrees of freedom and identifying an appropriate design requires much trial and error. (We do not want to discuss the design choices in detail here, as this is its own topic, but point to the respective works dealing with such problems, e.g. Haykin, 2009). Second, training ANNs can require considerable computational power. The computational demand rises more than proportionally with the number of units in network, because every new unit implies another weight factor to be learned for every link-neighbor. In the case of financial markets and the respective models, the problem becomes even worse because the network must be retrained often as the behavior of prices is not necessarily constant but new systematic patterns may emerge. To guarantee that traders can identify some pattern at the moment it becomes established, retraining must even be done periodically. Third, the ANN(s) usually appears as a “black box” to the observer. The transparency of the model and its dynamics is reduced.

2.3 Necessary and Convenient Model Features

The techniques and building blocks presented up to now can be the cornerstones of a model in which systematic patterns are removed endogenously. Yet, in the model presented in the following, their implementation brings about the need for other specific model features. In the following, we provide an overview of the necessary and convenient features of that model for the endogenous removal of systematic patterns. The necessary features have already been explained:

(1) Pattern exploiters

At least some traders must be able to identify the patterns to be removed and trade on them.

(2) Appropriate price setting mechanism

Price setting can be modeled in different ways, but some of them, e.g. a stylized market maker, do not necessarily lead to the reduction of the patterns exploiters are trading on. Computing equilibrium prices has been shown to be an appropriate approach to this end.[40]

The two conditions described are necessary for the endogenous removal of regularities. However, their fulfillment may still lead to problems concerning the implementation of pattern exploiters and the resulting model dynamics. To prevent these problems, two model features turn out to be convenient.

(3) Fundamental news

In the proof of proposition 1 it has been shown that, if systematic patterns in prices are removed, changes of prices can only be due to true news. This implies that if no news occurs, $P_{t+1} = P_t, \forall t$. Put differently, pattern exploiters tend to drive the market towards its steady state, countering endogenous market dynamics. To preserve dynamic complexity, true news is required. The implementation of a news arrival process can be achieved by a reality-oriented reproduction of the evolution of the fundamental value. The fundamental value of an asset is usually regarded to follow a random walk (Fama, 1965, and followers). Adopting the random walk approach for the fundamental value F_t prevents the model from converging on its steady state. In contrast, setting F_t constant, as practiced by many modelers, is an unfavorable simplification in the context of pattern exploitation.

(4) Discrete time

Formulating the model in discrete time solves a purely technical difficulty. Perfect removal of regularities requires their identification at the moment they are established. In a continuous-time model this would create immense computation costs, in particular if using ANNs. The discrete time approach reduces the computation time and thus enhances the tractability of the model.

[40] Of course, this is still a simplification of price formation in real markets. For example, in stock markets prices are usually formed by the matching of sell or buy requests listed in an order book. Evidently, this mechanism is also appropriate for the removal of patterns although the market is not necessarily in equilibrium for the last trading price.

3 APPLICATION

This section introduces a simple financial market model in which systematic patterns tend to arise mainly through the activity of trend followers. The simulations demonstrate that pattern exploiters effectively identify and trade on these patterns, leading to a model dynamics which again evolves unpredictably. Further results concern the effect of pattern exploiters on market efficiency.

3.2 The Model

The model introduced next can be interpreted as an adaption of the deterministic framework of the model presented in Dieci & Westerhoff (2006), which is based on the fundamentalist-chartist approach. The framework mentioned is an appropriate basis to illustrate the effect of pattern exploiters for four reasons: (i) it is relatively simple, (ii) it is formulated in discrete time, (iii) it produces systematic patterns in prices, (iv) it includes a profit-based switching mechanism between strategies by which some interesting emergent phenomena can be uncovered. Major differences of the model introduced here compared to Dieci & Westerhoff (2006) concern the following aspect.

- *Pattern exploiters.* Pattern exploiters who behave in the way described in Section 2.1 are introduced as an additional third trader group.
- *2-day moving average prediction of chartists*. Compared to the simple extrapolation of the most recent trend, the 2-day moving average prediction adds an additional variable (P_{t-2}), causing a more complex systematic pattern.

The other differences are due to the realization of the requirements identified in Section 2.3:

- *Random walk of the fundamental value,* instead of constant value.
- *Equilibrium pricing,* instead of market maker approach.

The resulting model consists of four major components: the expectation formation, the demand formulation, the switching mechanism, and the mechanism of price and value formation. The components interrelate according to the following logic: In each period, traders formulate their demand relative to their expectation about the price in the next period. Price expectations are formed according to different trading strategies: a fundamental rule, technical trend extrapolation, and sophisticated pattern exploitation. Furthermore, traders switch between these strategies. A strategy is the more popular, the more profits it has generated in the past. Finally, prices are formed such that demand and supply are equal. In a formal fashion, the model can be described as follows:

3.2.1 Expectation Formation

At each time t, traders form an expectation about the price of the asset in the next period. For fundamentalists this expectation is

$$E_t^F[P_{t+1}]|P_t = P_t + \kappa(F_t - P_t) \tag{9}$$

which stipulates that fundamentalists expect prices to adapt to the fundamental value to some degree specified by the parameter κ ($\kappa \in]0;1]$).

Chartists believe trends will continue. To identify trends, moving averages are computed (Brock & Hommes, 1998). In our model, chartists rely on the 2-day weighted moving average. Their expectation then results from the extrapolation of this trend, formally:

$$E_t^C[P_{t+1}](P_t) = P_t + (2r_t + r_{t-1})/3, \tag{10}$$

where r_t represents the most recent return in *t*: $r_t = P_t - P_{t-1}$. Due to their extrapolative expectation and the resulting demand, chartists induce positive feedback into the dynamics of prices, and thus create a source of systematic patterns of prices.

Pattern exploiters compute their expectation analogue to eq. (4) in Section 2.1. For simplicity, we assume that exploiters do not expect the law of motion g_t to change from *t* to *t+1*. Hence, instead of $\widehat{g_{t+1}}_t^X$, we can write $\widehat{g_t}_t^X$, or in short, $\hat{g}_t^X$. This leads to:

$$E_t^X[P_{t+1}]|P_t = \hat{g}_t^X\ [\Phi_t^X](P_t) \tag{11}$$

The information set Φ_t^X will be specified in Section 3.2. Note that the expectation about P_{t+1} is a function of the price P_t.

3.2.2 Demand Formulation

Each trader group derives their demand from the expected return $E_t^i[r_{t+1}]|P_t = E_t^i[P_{t+1}]|P_t - P_t$. For any transaction price P_t they buy, if for P_t they expect a following price rise ($E_t^i[r_{t+1}]|P_t$ positive) and sell if they expect a price fall ($E_t^i[r_{t+1}]|P_t$ negative). Assuming a linear function, this logic can be expressed as

$$D_t^i(P_t) = \alpha^i\left(E_t^i[r_{t+1}]|P_t\right) \quad i \in \{F, C, X\}, \tag{12}$$

where $D_t^i(P_t)$ is the net demand of trader group *i* at price P_t, and α^i represents a positive reaction parameter, as explained in Section 2.1.

3.2.3 Switching Mechanism

The switching mechanism relates to the switching of traders between strategies. A popular assumption is that a strategy tends to gain (/lose) followers if it produces more (/less) profits than alternatives (Brock & Hommes 1997, 1998, Hommes 2001). In Westerhoff & Dieci (2006), the weight of some trader group, respectively strategy i and time *t,* denoted w_t^i, is determined by i's attractiveness in *t,* denoted A_t^i, in the following fashion:

$$w_t^i = \frac{Exp[\gamma A_t^i]}{\sum_i Exp[\gamma A_t^i]}, \tag{13}$$

where γ is a constant rationality parameter that regulates the sensitivity of traders' reaction to a shift of the level of the attractiveness of a particular strategy. The attractiveness A_t^i represents a stylized moving average over past profits:

$$A_t^i = \eta A_{t-1}^i + r_{t-1} D_{t-2}^i. \tag{14}$$

$r_{t-1} D_{t-2}^i$ represents the value change of the long/short position built up, based on strategy i at price P_{t-2} due to the price change from *t-2* to *t-1*. The influence of this most recent profit for A_t^i relative to preceding profits stored in A_{t-1}^i is greater, the lower the positive parameter η. In this sense, η reflects agents' memory.

Technically, the switching mechanism defined above produces alterations in the model structure, because it implies changes of the state variables A_t^i. As in reality, these structural changes can lead to the emergence of new systematic patterns while others disappear. To discover new patterns, traders have to remain in a permanent state of alertness and learn continuously. Vice versa, simply relying on old patterns to persist is not optimal to maximize profits.

3.2.4 Price and Value Formation

The mechanism of price adaption is equal to the equilibrium pricing principle, specified by equation 5. The total demand, denoted $D_t(P_t)$, results from the weighted sum of the net demand of all trader groups i:

$$D_t(P_t) = \sum_i w_t^i D_t^i(P_t), \qquad i \in \{F, C, X\} \tag{15}$$

For the fundamental value, we adopt the random walk assumption:

$$F_t = F_{t-1} + \Upsilon_t \qquad ,\Upsilon_t \in N(\mu_i, \sigma_i^2) \tag{16}$$

Υ_t stands for changes of value caused by fundamental news emerging after *t-1* and not later than *t*. These value changes are IID normally distributed with mean μ and variance σ^2.

Note that the model market specified above complies with the requirements identified in Section 2.3. Hence, the necessary and convenient model features for the endogenous removal of systematic patterns are given.

If we abstract from pattern exploiters, the law of motion of prices results from a combination of eqs. (5), (8), (9), (10), (11), and (14):

$$P_t = g_t(\Phi_t) = \frac{3w_t^F \kappa \alpha^F}{Z} F_t - \frac{w_t^C \alpha^C}{Z} P_{t-1} - \frac{w_t^C \alpha^C}{Z} P_{t-2} \tag{17}$$

with $Z = 3w_t^F \kappa \alpha^F + w_t^C \alpha^C$. The law of motion is equivalent to the function $g_t(\Phi_t)$. The input for this function is given by the information set Φ_t, which is here $\Phi_t = [F_t, P_{t-1}, P_{t-2}]$. Hence, any pattern exploiter could exploit the deterministic features perfectly if she knew g_t and Φ_t. Still, the active intervention of pattern exploiters will influence the function g_t, and possibly extend Φ_t by other fundamental or technical information. For the latter to occur, it is sufficient that pattern exploiters believe this information to be relevant and react to it. The identification and exploitation of patterns is thus a recursive process, in which the actual law of motion of prices changes.

3.2 Model Calibration

The calibration of the model refers to two aspects: the setting of the parameters included in the model equations and the specification of pattern exploiters.

3.2.1 Parameter setting

Table 1 gives an overview of the model parameters and their settings. The parameter setting of the switching mechanism, γ and η, was adopted identically from Westerhoff & Dieci (2006). σ is set to 1%, which should be a reasonable assumption for the volatility of the fundamental value. The reaction coefficients of trader groups could be set rather freely as there is no empirical data for these values. Setting $\kappa\,\alpha^F = \alpha^C = 1$ might be the most salient assumption, which further generates a stable model dynamics. α^F can be regarded as the independent variable which regulates the influence of pattern exploiters and, hence, the degree to which pattern will be removed.

Parameter	Description	Value
$\kappa\,\alpha^F$	reaction intensity of fundamentalists	1
α^C	reaction intensity of chartists	1
α^X	reaction intensity of pattern exploiters	10
γ	rationality of strategy choice	350
η	weight of agents‘ memory	0.975
σ	Standard deviation of changes of fundamental value	0.01

Table 2: The model parameters and their setting

3.2.2 Pattern Exploiters

Pattern exploiters should be configured such that they are able to identify the true behavior of the deterministic model as specified by the law of motion $g_t(\Phi_t)$ (eq. 17). As $g_t(\Phi_t)$ is linear here, it can be represented perfectly by a linear prediction model. According to the independent variables of $g_t(\Phi_t)$, Φ_t^X is set to $\Phi_t^X = \Phi_t = [F_t, P_{t-1}, P_{t-2}]$. This yields the prediction model specified by eq. (8). The model is realized technically by an ANN with no hidden layer. In each period *t*, the regression coefficients, respectively weight factors β_1 to β_3, are learned using the last 50 pairs of independent and dependent variables. The root mean squares are computed as the error criterion. [41]

3.3 Measures of Predictability

In general, a process complying with ASP (Absence of Systematic Patterns) is called a martingale. In discrete time, a martingale can be defined as a stochastic process with observations $X_1, X_2, \ldots$ for which $E[X_t] < \infty$ and $E[X_{t+1}|X_1, X_2, \ldots, X_t] = X_t$, that is, all preceding observations do not contain any evidence to believe that the next observation will be greater or smaller than the last one. In this sense, the process is unpredictable. The ASP property includes the AA property (Absence of significant Autocorrelations), meaning that autocorrelations between changes $X_t - X_{t-1}$ tend towards zero for all lags τ as the number of observations rises. The autocorrelation $R(\tau)$ between the return in *t* and the return in $t - \tau$ is computed as:

$$R(\tau) = \frac{E[(r_t - \mu)(r_{t-\tau} - \mu))]}{\sigma^2}, \tag{18}$$

where σ^2 is the variance of returns observed. The existence of significant autocorrelations indicates the existence of systematic patterns in price dynamics. The reverse conclusion, however, does not necessarily hold. Though AA might be fulfilled, complex patterns in prices may still be present, such that ASP is violated. Ignoring this aspect, financial market models usually limited themselves to the $R(\tau)$ indicator. For the goal of the present study, however, advanced indicators able to identify more complex patterns are needed. These indicators are provided by Challet (2005), who introduces two conditional measures of predictability.

The first one, *H*, applies the mean return conditional to different patterns in prices. With *S* being the number of relevant patterns θ ($\theta = 1, \ldots, S$), *H* can be formulated as

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[41] Choosing the right learning horizon implies dissolving a trade-off. Increasing the learning horizon provides more information to exploiters but enhances the probability that a law of motion is learned which is no longer valid.

$$H = \frac{1}{S}\sum_{\theta=1}^{S}\langle r|\theta\rangle^2 \tag{19}$$

The intuition of H is that in a market which is completely unpredictable, a certain pattern in prices, e.g. a price rise, should not give any information about the return in the next period, i.e. the mean return following this pattern tends to zero. H averages these mean returns over a set of patterns which are believed to be relevant. A higher H points to a greater predictability of price dynamics.

Still, the indicator H does not capture all aspects of predictability as it misses predictability associated with oscillatory behavior. The latter can be identified by the third indicator, the conditional price return auto-correlation function $K(\tau)$. It can be written as:

$$K(\tau) = \left(\frac{1}{S}\sum_{\theta=1}^{S}(R(\tau)|\theta)\,\sigma^2 - H\right)/\sigma^2, \tag{20}$$

where $R(\tau)|\theta$ is the correlation of price returns subsequent to occurrences of pattern θ.

As traders do not include more than the last two prices into their trading calculus, any predictability of P_t can be derived from $[F_t, P_{t-1}, P_{t-2},]$. Therefore, $\tau \in [1, 2]$ will be investigated. (Challet (2005) limits himself to $\tau = 1$). To compute H and $K(\tau)$, four patterns θ_k, are considered as relevant: $\theta_1: r_t > 0$, $\theta_2: r_t < 0$, $\theta_3: (2r_t + r_{t-1})/3 > 0$, $\theta_4: (2r_t + r_{t-1})/3 < 0$. By representing a price rise and a price fall, respectively, θ_1 and θ_2 might be regarded as the simplest patterns possible. θ_3 and θ_4 are derived from the trading philosophy of chartists, as they stand for a positive and negative two-day moving average, respectively. Hence, if the trading behavior of chartists penetrates the dynamics of prices such that predictability is caused, this predictability should be reliably captured by H and $K(\tau)$.

3.4 Simulation Results

To understand the influence of pattern exploiters, it is fundamental to understand the model when these traders are absent. Therefore, we begin by simulating a basic framework in which only fundamentalist and chartists are active.

3.4.1 The Model without Pattern Exploiters

Figure 1 shows the dynamics of model. The upper panel illustrates the price P_t (black) and the fundamental value F_t (gray). In principal, we observe excess volatility − prices evolve in a more volatile manner than value. More specifically, prices appear to be driven by certain momentum leading to fluctuations around value. The reason for this behavior is the interplay of trading strategies: Reacting to fundamental news, fundamentalist cause a movement of prices towards value. Technical traders interpret this movement as the beginning of a trend, and trade on it, thereby inducing momentum into the dynamics of prices by which prices overshoot value. The trend reverts once the mispricing is sufficiently great such that fundamental orders outweigh chartists, upon which the loop repeats.

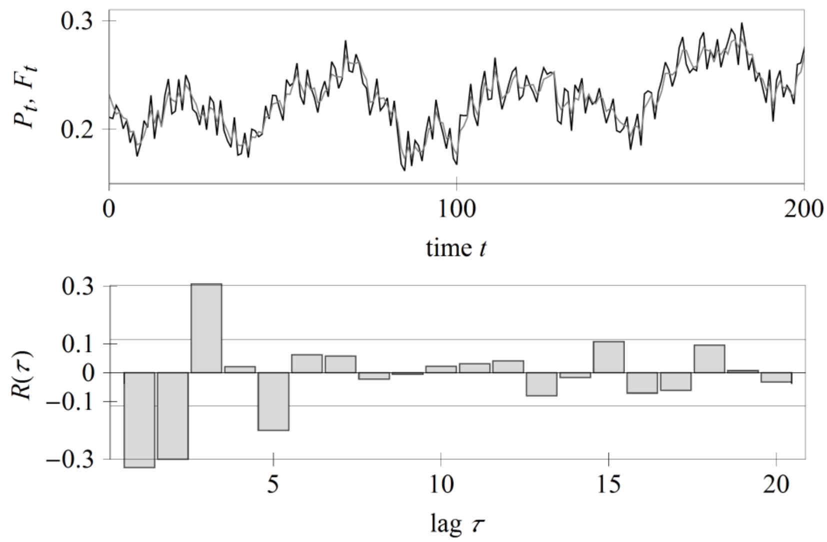

Figure 1: Price and value (top), and autocorrelation of returns (bottom) without pattern exploiters. Autocorrelations based on 10,000 simulation periods.

The fluctuation of prices around value is a simple example of a systematic pattern in the dynamics of prices. It is simple, as it is captured well by the autocorrelation of returns. The autocorrelations $R(\tau)$ for different lags τ are indicated by the bottom panel, with the gray horizontal lines indicating the 1% level of significance. The panel shows that the basic framework produces great autocorrelations on the first two lags. The reason is that in eq. (9), chartists extrapolate the trends of the last two periods. For the third and fourth lag, the autocorrelations turn positive, which reflects the trend reversal due to fundamental trading. For the other lags, the scheme repeats. Formally, this pattern has been described by eq. 18.

Note that in a market with fundamentalists only, $P_t = F_t, \forall t$. This can be verified by simply combining eq. 5, 8, 11, and 14, meaning that systematic patterns in prices would be absent. From this perspective, the existence of the patterns can be attributed to the activity of chartists.

3.4.2 The Model with Pattern Exploiters

Next, pattern exploiters enter the market. To begin with, we conduct a series of runs in which patterns exploiters merely observe the dynamics of the deterministic model before and merely form predictions about prices – exploiters do not influence the dynamics themselves. Then, we measure the average prediction error of trader groups i, defined as $\varepsilon^i = \frac{1}{T}\sum_{t=1}^{T}\left|E_t^i[P_{t+1}] -\right.$

$P_{t+1}|$. We find that, due to their artificial intelligence, exploiters are able to predict prices most accurately. (For the exemplar run, we get $\varepsilon^X = 11.67 * 10^{-3}$)[42]. Fundamentalists, who believe prices to follow value, perform second best ($\varepsilon^F = 11.75 * 10^{-3}$), because the fundamental value is indeed the main anchor for the evolution of prices. However, fundamentalists ignore the predictive power of past returns and, thus, miss part of the information determining the evolution of prices. Chartists, who believe in the persistence of trends, commit the greatest prediction errors ($\varepsilon^F = 16.67 * 10^{-3}$), as with the fundamental value they ignore the most important determinant of prices. These results confirm that the prediction models of exploiters actually work. Furthermore, their superior prediction power potentially enables exploiters to achieve superior profits which potentially lead to a greater weight w_t^X.

Figure 2 depicts an exemplary simulation run in which exploiters actively participate in the market and their reaction intensity α^X is set to 10. The upper panel shows that prices have stopped fluctuating around value; at first glance, the systematic pattern in price seems to have disappeared. The third panel, which shows the autocorrelations of returns, confirms that the predictability of prices has dropped. Autocorrelations between returns are considerably lower compared to the run without exploiters. Nevertheless, significant autocorrelations are still present. These observations indicate that exploiters successfully exploit systematic patterns. However, their trading volume is still too low to remove patterns entirely.

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[42] Note that a predictor who knows g_t and Φ_t would still commit prediction errors because P_{t+1} is determined by g_{t+1} and $\Phi_{t+1} = [F_{t+1}, P_t, P_{t-1}]$ which are still unknown in *t*. Example: Under the assumption that market efficiency is perfect such that $P_t = F_t$, the best prediction for P_{t+1} would be P_t. The resulting prediction error ε^i would then correspond to average absolute change of value $(1/T)\sum_{t=1}^{T}|Y_t|$. The latter can be computed as $\left(\frac{1}{T}\right)\sum_{t=1}^{T}|Y_t| = \sqrt{2/\pi} * \sigma \approx$ (with $\sigma = 0.01$) $7.98 * 10^{-3}$ (Goldstein & Taleb, 2007). $7.98 * 10^{-3}$ can thus be interpreted as the minimum achievable for ε^i as the number of observation tends towards infinity. Nevertheless, in the present model this value can hardly be reached. The reasons is changes of the state variables A_t^i, i.e. changes of the model structure, continuously alter the law of motion via the weights w_t^i. Exploiters estimate the law of motion from historical data. Changes of the law in the meantime will thus lead to systematical errors.

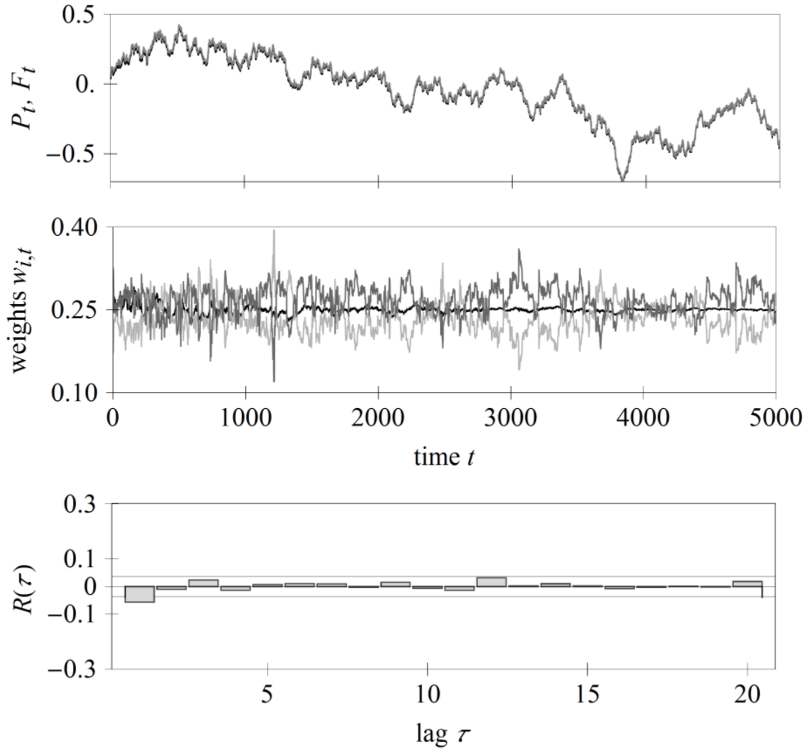

Figure 2: Typical simulation run with pattern exploiters.

The second panel depicts the weights of trader groups i. Two important insights are conveyed. First, the weight of exploiters (dark gray) on average exceeds the weight of fundamentalists (black) and chartists (light gray). Further, the weight of fundamentalists and the weight of chartists move in opposite directions to each other. The reason is that the beliefs of exploiters and chartist diverge greatly: chartists believe that trends will continue, whereas exploiters know that such patterns are almost always absent. Therefore, exploiters and chartists trade with each other, and, due to the great trading power of exploiters $\alpha^X = 10$, with great volume. However, as the prediction accuracy of exploiters ($\varepsilon^X = 8.77 * 10^{-3}$) is significantly higher than the one of chartists ($\varepsilon^C = 11.17 * 10^{-3}$), exploiters gain money from these transactions whereas chartists lose. As for every buy, there is one sale (eq. 14), the gains of exploiters mirror the losses of chartists. Because the weights of groups are dependent on profits, this leads to the mirror-inverted dynamics of both weights. In sum, pattern exploiters exploit those traders who are responsible for the emergence of systematic patterns.

The second insight is that the weight of exploiters does not remain on a certain level but goes up and down. To understand the cause, assume that a systematic pattern is present which is identified by exploiters. Then, exploiters will start to trade on the pattern, and thereby achieve superior profits compared to other traders. Due to the superior profits, the weight of exploiters tends to rise. However, the more exploiters are in the market exploiting the particular pattern, the more the pattern is reduced. Thereby, the opportunity for exploiters to achieve superior profits diminishes and their weight tends to fall again. (In an extreme case, the dynamics of prices is completely unpredictable. Hence, profit opportunities are equal no matter if a trader buys or sells). The withdrawal of exploiters makes it possible that systematic patterns reappear, and the loop repeats itself. In conclusion, the activity of exploiters undermines their own superiority, and thereby opens the door for the survival of other, less informed and/or less intelligent traders. (Another reason for the variations in weights is that in some periods, prices indeed follow trends, simply due to a random trend of the fundamental value. Hence, the predictions of chartists are sometimes relatively good).

The exemplary run described above has confirmed the potential of our approach; systematic patterns are reduced successfully by the activity of intelligent traders. As a second step, we conduct a systematic analysis of the influence of these traders on market predictability. The results are displayed in figure 3. The setup of the large data experiment is as follows: We simulate the model with fundamentalists, chartists, and exploiters. The reaction parameter of exploiters α^X represents the independent variable which is either set to 0, 1, 5, or 10. For each value of α^X, 100 runs with 5,000 periods each have been simulated, including an initial transition period of 1,000 periods which has been rejected. The dependent variables are given by the indicators of predictability introduced in Section 3.3. The results are summarized by Box-Whisker-Plots. The bottom (top) of the box represents the 25th (75th) percentile. The mid vertical line represents the median and the black dot the mean. The upper (lower) end of the whisker indicates the minimum (maximum) observation.

The experiments show that all measures of predictability, including the measures of conditional predictability, H and $K(\tau)$, are continuously decreasing due to a greater influence of exploiters as specified by α^X. For greater settings of α^X, there are several runs in which predictability measures are not significant anymore. In conclusion, the predictability of prices can be reduced effectively, up to their disappearance, by traders who recognize the behavior of prices and trade on the patterns found.

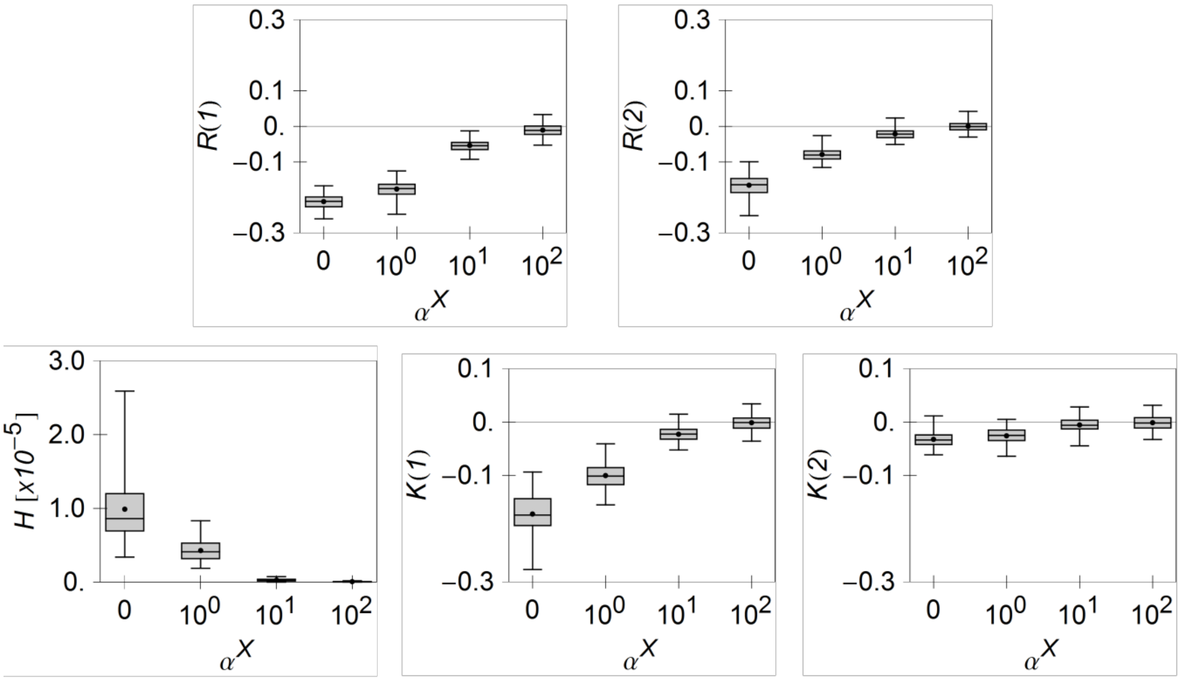

Figure 3: Summary statistics − measures of predictability. 1% level of significance indicated by gray horizontal lines.

Let us conclude by examining some remarkable incidental results on the influence of pattern exploiters on market efficiency. Figure 4 depicts three indicators of efficiency:

- *Market distortion, D:*

  $D = \frac{1}{T}\sum_{t=1}^{T} D_t,$ $\quad$ *with* $D_t = |P_t - F_t|,$ (21)

  where T stands for the number of observations. D captures the tendency of price to reflect value in terms of the absolute average mispricing.

- *Excess volatility,* V^{ex}*:*

  $V^{ex} = \frac{1}{T}\sum_{t=1}^{T} r_t^{ex},$ $\quad$ *with* $r_t^{ex} = |r_t| - |F_t - F_{t-1}|.$ (22)

  V^{ex} compares shifts of prices and fundamentals, where r_t^{ex} can be interpreted as the excess return. If prices tend to overreact (/underreact) to fundamental news, V^{ex} is positive (/negative).

- *Ratio of correct price reactions, C:*

  $C = \frac{N}{T}.$ (23)

  where N is the number of returns r_t with $sgn[r_t] == sgn[F_t - F_{t-1}]$. C captures the degree to which prices react to fundamental news.

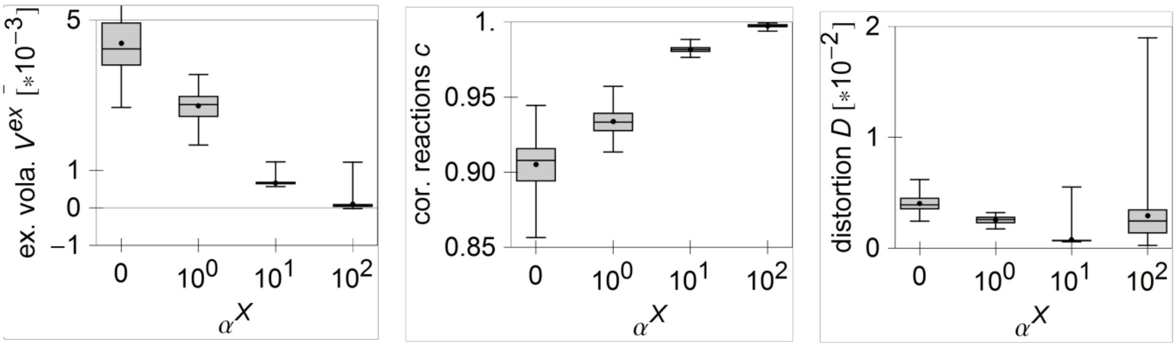

Figure 4: Summary statistics – market efficiency.

The results show that the effects on market efficiency are complex. On the one hand, market efficiency is improved as the tendency of prices to reproduce changes of fundamentals increases – a greater α^X leads to an increase of C rises and a decline of V^{ex}. The reason is that, the more exploiters remove patterns, the more the fundamental value tends to be the only determinant of prices, and this is noted again by exploiters. As a result, exploiters tend to turn to fundamentalists, who only react to fundamental news. (With reference to the prediction model defined by eq. (17), the regression coefficients β_2 and β_3 tend to 0). This also leads to a decline in market distortion. On the other hand, if α^X becomes very great, distortion tends to rise with relatively great variance between simulation runs. This result is due to the fact that pattern exploiters, in contrast to fundamentalists, do not trade on mispricing per se, but identify the fundamental value as the main determinant of prices. However, if α^X becomes relatively great, the dynamics of prices is driven mainly by exploiters who, thus, learn from themselves. This complicates an adequate estimation about the influence of fundamentals. As a result, discrepancies between the levels of prices and value can emerge. (With reference to the prediction model, β_1 deviates from 1).

Note that the positive effects of pattern exploitation on market efficiency are dependent on the condition that exploiters recognize the true behavior of prices. It would be also possible that exploiters identify pseudo-patterns. In this case, exploiters adopt noise-trader behavior as they "trade on noise as if it were information" (Black, 1986). The identification of pseudo-patterns can occur, if exploiters do not know all the variables actually determining the evolution of prices (for example, exploiters could be interpreted as purely technical traders who do not know the fundamental value) or if they misinterpret dynamics of prices (for example, if exploiters consider relatively narrow time ranges, patterns might appear to be systematic which are in fact random). Experiments with such agents have shown that the trading on pseudo-patterns destabilizes market dynamics and leads to the emergence of typical stylized facts such as volatility clustering or heavy tails in the distribution of returns. However, as these phenomena lay beyond the focus of the present study, we leave a closer examination to future research.

4. CONCLUSION

In financial market models, the absence of systematic patterns in prices – an important stylized fact of real markets – is usually replicated by means of stochastic components. The present article has introduced a model in which systematic patterns are eliminated endogenously and in a reality-oriented fashion. This is achieved by the activity of intelligent traders who are able to identify the patterns in prices and exploit them. With perfect knowledge, regression techniques and artificial neuronal networks, three methods for the pattern identification and forecasting of model agents have been discussed. In the present model, a linear prediction model is used, which can be interpreted as the simplest form of an Artificial Neural Network (ANN). As ANNs are technical reproductions of the human brain, they might be regarded as quite an accurate way of modeling the cognition of financial traders. The simulation experiments confirmed that if the trading power of pattern exploiters is sufficiently great, systematic patterns disappear completely and prices evolve unpredictably. In sum, we believe the model to reproduce the mechanisms of pattern detection, exploitation and reduction quite realistically. An explanation for the putative unpredictability of prices and, in particular, the absence of autocorrelations in returns seems to be given.

As incidental results, pattern exploiters, who trade on the true behavior of prices, were found to improve market efficiency as the tendency of prices to replicate fundamental news increases. Yet price distortion may rise if the trading power of exploiters relative to fundamentalists becomes overwhelming.

Needs and potential for future research are various. When developing the model, the focus was on the endogenous removal of systematic patterns. Other typical statistical properties of financial market dynamics (surveys by Guillaume et al., 1997; Cont 2001), such as volatility clustering or heavy tails in the return distribution, are left beyond consideration. Experiments have indicated that these stylized facts can emerge if pattern exploiters trade on pseudo-patterns as their information level or intelligence is not sufficient to interpret the behavior of prices correctly. These insights and the methods described here could lead to a model which replicates the stylized facts of financial markets, including the unpredictability of prices, without exogenous noise being added.

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5

High Frequency Trading and its Influence on Market Dynamics: Insights from Agent-Based Modelling

Björn-Christopher Witte

Abstract: Within the last decades the weight of High-Frequency (HF) trading in global financial markets has risen continuously. HF-trading denotes transactions made by computers with reaction speeds in the domain of microseconds and average holding periods of several minutes. This study investigates the impact of HF-trading on financial market dynamics by agent-based modelling. In contrast to some previous studies that treat HF-traders as a rather homogenous group, we believe that the influence of HF-traders is dependent on the strategy they apply. Accounting for this several strategies are investigated: market making, trend-following, mean-reversion, event-trading, and noise trading. As special properties of the model, simulation runs represent singular days and, due to the event-driven approach, events can occur at arbitrary moments of time. As main findings, the simulation experiments show the aggressive strategies to have a lower effect on market dynamics if used by HF-traders than by the respective low-frequency group. The reason is differences in inventory control between both groups. Surprisingly, the market is destabilized by HF-market makers, because the lower bid-ask spreads facilitate technical intraday trading. These results suggest that, at least for aggressive strategies, the impact of speed alone is lower than expected. What matters more are the strategy of traders, their trading volume, and the intensity of inventory control.

Keywords: High frequency trading; agent-based modelling; market maker; simulation, market efficiency.

JEL classification: G17; G28.

1. INTRODUCTION

It is already more than 40 year ago when in 1971 the NASDAQ, the first electronic stock market, was set up – a revolution, since with electronic trading the physical distance between investors lost importance and trading became fast and anonymous. The digitalization of trading also opened the way for a second technological revolution which followed almost instantly: The advent of the so-called algorithmic trading (AT). Trading did no longer require the initiative of human beings, but computers have started to make investment decisions rigorously following the strategies coded. High-frequency (HF) trading can be regarded as a "technological evolution" (Haldane, 2011) of AT which shifted the standards of financial trading. HF-trading is a type of AT as it is necessarily executed by computers. However, HF-traders do not merely automate trading but seek to take profits from the shear speed of data processing and transmission, for example, by exploiting marginal opportunities for arbitrage which only exist for fractions of a second. Since only the fastest ones are able to earn such profits, speed has become a competitive edge. Whereas one decade ago execution times dropped below one second, today 10 micro-seconds define the lower limit. A "race to zero" (Haldane, 2011) has begun, in which local distance has gained importance again, as even the length of the cables linking the servers of HF-traders to the trading platform has become a critical determinant of speed.

Together with speed, the presence of HF-traders in markets has risen steadily in recent years. According to Haldane 2011, the share of HF-trading was less than a fifth of turnover on NYSE-equity market in 2005 but escalated to more than two thirds in 2011.[43] In Europe, HF-trading accounts for over 35% of the equity market. Due to the large share of trading coming from HF-traders, it is reasonable to assume that this group has a significant impact on market dynamics and efficiency. This has disembogued into a series of conjectures. Opponents view HF-traders as aggressive traders. They would increase intraday volatility (1); lead to a rising Hurst Index (2); increase the correlation between stocks, which raises the intensity of turbulence to spread across assets and markets (3); and operate at the expense of fundamental investors (4). Supporters state that HF-traders would often act as market makers and supply the market with additional liquidity (5). Thereby they reduce bid-ask spreads and transaction costs for ordinary investors, and contribute to price discovery (6). Finally, authorities

[43] Confirming this number, Brogaard (2010) reports that HF-traders participate in 68.5% of the dollar-volume on the U.S. equity market The figure is computed from Nasdaq data stemming from one week in 2010. In the financial-times article, "SEC runs eye over high-speed trading," the share of volume due to HF-traders is approximated to be at 73% (Financial Times, July 29, 2009).

speculate if market making will increasingly congregate around HF-trading (7) (Zhang 2010; Haldane, 2011).

Further, it is questioned whether the positive liquidity effect persists in times of market stress, when large volatility increases the risk for liquidity providers and a flood of trading signals might trigger a rather aggressive behaviour of HF-traders. The flash crash is sometimes referred to as a warning example in this context. On may 6th, 2010, the DOW-Jones Industrial Average collapsed by about 9 percent in just 5 minutes, only to recover almost completely as trading on the E-Mini had been suspended for five seconds. Subsequent research showed that the dive was caused actually by fundamental selling. However, HF-traders might have acerbated it by their quick and automated reaction to the heavy trading signal (See Kirilenko et al., 2011; Easley et al., 2010; as well as the joint SEC and CTFC report, September 30, 2010: "CFTC-SEC Findings Regarding the Market Events of May 6, 2010"). Johnson (2012) sets the Flash Crash into the context of ultrafast "black swan" events, and provides an empirically analysis of the transition from human-machines phases to all-machine phases.

Yet, for some the Flash Crash is not more than the eye-catching peak of an iceberg of more lingering changes, financial market dynamics have undergone in recent years.

(1) Using S&P 500 data from 1990 to 2010, Haldane (2010) finds that correlations between stocks within and across markets and platforms have risen significantly when comparing the period from 1990 to 2005 with the one from 2005 to 2010. Lehalle et al. (2010) measure the correlations between any pair of assets listed in the major world indices[44] and arrive at a similar result: From about 2000, a clear rise in correlations is observable.

(2) Times of high correlations between stocks tend to coincide with times of pronounced market volatility. This relationship has become more significant in recent years (Lehalle et al., 2010; Haldane, 2011).

(3) Exploring NYSE and Nasdaq intraday data of 14 US stocks from January 1, 2002 to May 31, 2009, Smith (2010) finds that the Hurst coefficient for price changes over 15 minutes and less has increased significantly since around 2005. A greater Hurst

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[44] These include (DAY, CAC 40, CLES 60, IBEX 35, TOPIX top 150, NASDAQ 100+ DJIA)

coefficient points to fatter tails in returns and heavier volatility clustering. Abnormal market behaviour seems to occur in ever smaller chunks of time.

Since the upcoming of HF-trading coincides well with the developments mentioned above, and due to other reasons, HF-trading is often believed to be one of their origins.

Research on the effects of high frequency trading on market dynamics and efficiency is still very fresh and relatively scarce. Moreover, the findings sometimes diverge, in particular with regards to the impact of HF-trading on price volatility. (Studies suggesting a detrimental effect include Zhang, 2010, and Cartea and Penaleva, 2011). The opposite is found by Broogard, 2010, and Hasbrouck, 2011).

A central credo of the authors of this study is that the heterogeneity of the results on the effects of HF-trading is due to the fact that the group of HF-traders is heterogeneous in itself. “HF-trading is far from homolithic”, but comprises a range of strategies (Haldane, 2011). Some of these strategies are passive and provide liquidity, other are aggressive and take liquidity from the market. Therefore, one should be very carefully if making statements about the influence of HF-traders in general. Rather, for the purpose of a more differentiated analysis, different ways of behaviour require to be analyzed separately. The present article aims in this direction.

The principal research method applied in our study is agent-based modelling. Agent-based models (ABMs) of financial markets have proven to be a helpful tool to understand typical phenomena of financial market dynamics, e.g. fat tails in returns and volatility clustering. Moreover, the models can be used as artificial laboratories to test the influence of policy measures or the impact of different investment strategies. In the present article an ABM is developed that allows well to explore differences in trading speed, as simulation time is virtually continuous. The model is fitted quantitatively to the equity of Lloyds plc, one of the most traded assets at the London Stock Exchange (LSE). Eight validation criteria are used, of which three relate to market infrastructure (the bid-ask spread, the number of trades, and trading volume) and the other five cover to the dynamics of prices (including the Hurst coefficient). The trading strategies tested comprise simple versions of market making, fundamental and mean reversion trading, trend extrapolation, and noise trading. Depending on the experiment, we vary the strategies applied and if the strategy is used by HF-traders or by regular day-traders. This approach allows isolating the effect of pure speed and the effect of a particular strategy, and, thereby, to achieve a more diversified picture about the consequences that HF-trading might have in practice. We seek to tackle the following research questions:

- How do different strategies typically applied by HF-traders affect indicators of market efficiency, such as liquidity and market risk?
- Does it make a difference if a particular strategy is applied in low or high frequency?
- Can we find relevant evidence for the conjectures on HF-trading?

The simulation experiments yield several relevant findings. Aggressive strategies produce a lower effect for market efficiency if applied by LF-traders, but for HF-traders the effect is relatively low. The reason is the intense inventory control by HF-traders which forces them to reverse transactions quickly. This tends to offset the effect on market dynamics induced originally. Surprisingly, we find that HF-trading destabilizes financial market if used by market makers. HF-market makers quickly induce new liquidity into a drowning market, which lowers bid-ask spreads. Lower spreads foster technical intraday trading, which reinforces the fluctuations of prices. Other results relate to the conjectures about HFT. We find evidence that HF-trading leads to a rising correlation between stocks if and only if HF-traders act as event-traders. In contrast, we cannot confirm HF-traders to undermine fundamental investments. Further, the experiments show that HF-market maker gain superior profits in comparison to the respective LF-group. This suggests that market making might increasingly be performed by HF-traders. Some of these finding suggest that the speed of trading might play a minor role for market dynamics than expected. More important variables of traders are their trading strategy, their trading volume, and the intensity of inventory control.

The remainder of this article is organized as follows. In Section 2, we review the state of research on the consequences of HF-trading, and highlight possible reasons for the heterogeneity of findings. Section 3 introduces the agent-based financial market model. In Section 4, several indicators of market dynamics are defined, which will be essential for the validation of the model (Section 5) and for the simulation experiments (Section 6). Finally, Section 7 summarizes the most important findings, and highlights needs for future research.

2. PREVIOUS RESEARCH

As HF-trading is a quite fresh evolution in financial markets, research on its influence of market dynamics is relatively scarce, and many contributions are still in a working-paper state. When surveying these studies, two aspects become apparent. Firstly, the studies disagree on some effects, e.g. the impact of HF-trading on price volatility. Secondly, the studies follow different approaches to capture HF-trading. Since HF-trading is not directly observable, empirical studies need to devise a method to measure HF-trading, which implies to distinct between HF-trading and algorithmic trading in general. Model-driven studies have problems to account for the variety of strategies used by HF-traders. Usually, the models limit themselves to one particular way of behavior of these traders. This leads to very different interpretations of HF-trading between studies. The following survey of previous research should clarify these aspects.

In a pioneer work on HF-trading, Brogaard (2010) explores data about 26 HF-traders in the US-equity market, who account for more than two thirds of total trading volume. The results suggest the impact of the HF-traders on market quality to be positive. HF-traders reduce bid-ask spreads as they then tend to offer the best bids and offers, they “add substantially to the price discovery process” and “may dampen intra-day volatility”. Brogaard states that the HF-firms in his study mainly use a price reversal strategy driven by order imbalances. As a drawback, his approach does not allow to differentiate strictly between algorithmic and HF-trading. Hendershoot et al. (2011) focus on algorithmic traders. The authors seek to find out if this algorithmic trading has improved market liquidity by investigating NYSE data before and after a specific moment in 2003 when a technical change to the NYSE order book facilitated computer-based trading. Similar to Boogard (2010), the study confirms algorithmic trading to enhance market liquidity, narrow spreads, and to improve the “informativeness of quotes”. However, it is not clear if these effects are due to HF-traders or another form of algorithmic trading. Lehalle and Burgot (2010) refer to HF-trading in the context of the increasing fragmentation of European financial markets. Using data for the U.K. and Spain, they state that HF-trading would not increase intraday volatility. Zhang (2010) studies data of U.S. capital markets and arrives at a different conclusion. HF-trading would be positively correlated with price volatility. Moreover, “the positive correlation between HFT and volatility is stronger when market uncertainty is high, a time when markets are especially vulnerable to aggressive HFT strategies and to the withdrawal of HFT market-making activities.” Further, it is found that HFT acerbates price discovery. Based on order-level NASDAQ data, Hasbrouck and Saar (2010) seek to uncover HF-trading by identifying “strategic runs” – submissions, cancellations, and executions of orders in the millisecond domain. They find HF-trading to improve market quality in terms of short-term liquidity, spreads, and order book depth. These results apply for normal times and times of stress.

Evidence from model-driven studies dates back to Froot et al. (1992). The authors show that short-horizon traders deteriorate market efficiency, as they tend not to account for fundamental information. Cvitanic and Kirilenko (2010) construct an experimental asset market, in which low frequency traders are represented by human being and high-frequency traders by machines. In the study, HF-trading is interpreted as liquidity provision only. One of their findings is that in a market with a high-frequency trader, trading volume goes up and the ratio of extreme returns declines. Both results suggest market quality to improve. Cartea and Penalva (2011) design a model following Grossman and Miller (1988) but with HF-traders as intermediaries between aggressive traders and market makers. HF-traders are found to reduce the revenues of aggressive traders by deteriorating transactions prices. Further, HF-traders increase price volatility. The frictionless and competitive model market by Jarrow and Protter (2011) shows that HF-traders produce mispricing and this mispricing can only be exploited by themselves. In contrast to ordinary traders, who observe the price process and their trading strategies, the high frequency traders receive a common signal, which represents some market-related event or a mispricing. The advantage in speed of HF-traders is interpreted as the ability to trade instantaneously on their common signal.

A remarkable observation from the research review might be that model-driven studies state HF-trading to have a significantly worse impact on market quality than empirical analyses. A possible explanation is that models ignore relevant aspects of the behavior of HF-traders. Our study indicates that one of these aspects might be the strict inventory control by HF-traders, which mitigates their influence on market dynamics. Another explanation could be that the HF-strategies in the models do not represent the behavior of real HF-traders accurately. To isolate the effects of speed, inventory control, and trading strategies, we test different strategies which are either used by low frequency (LF) or HF-traders.

3. THE MODEL

In this chapter, we introduce an agent-based (AB) model of a stock market which allows implementing and exploring HF-trading. As agent-based modelling represents a relatively novel approach in financial market research, a brief overview of the field is given at first.

3.1 Agent-Based Models of Financial Markets

Originally stemming from social sciences, “in agent based modeling, a system is modeled as a collection of autonomous decision-making entities” (Bonabeau, 2002). Usually, an agent-based model is dynamic and subject to simulation experiments by means of computers. AB-modelling is by definition a bottom-up approach. By reproducing the behaviour of agents and their interactions, the model represents the structure of a system on the micro level. The simulation experiments then illustrate the resulting macro behaviour of the system as a whole.

Tesfation and Judd (2006) as well as Gilbert (2007) represent standard volumes on such models in social and economic applications. A typical goal of agent-based models is to uncover and explain "emergent phenomena" – properties of the system behaviour which are product of the interaction of the system components (agents). Social segregation would be a classical example (Schelling, 1969, 1971).

Since about 1980, AB-modelling has been employed successfully for research on financial markets.[45] Financial markets are well suited for AB-modelling as they represent social systems with traders being the system components who typically interact via financial transactions. Two major goals of application can be identified. First, the models can improve our understanding of typical "stylized facts" observable in financial market dynamics, such as bubbles and crashes or volatility clustering (e.g. Lux and Marchesi, 2000). Second, the models can be used as artificial laboratories, particularly to stress test trading strategies (e.g. Chiarella et al., 2006) or the effects of regulatory policies. Examples for the latter comprise transaction taxes (e.g. Westerhoff and Dieci, 2006), central bank interventions (e.g. Reitz et al. 2006), publication policies (e.g. Witte, 2010), or the Basel II framework (e.g. Hermsen, 2010). Westerhoff (2008) surveys studies of this domain.

Several advantages of AB-modelling compared to traditional methods (e.g. statistical analyses of empirical data) can be identified.

- Apart from limits due to computation time, the simulation experiments allow generating as much data as needed.
- Tests of various scenarios can be conducted which might be impossible or very costly to do in real or experimental markets.
- Causes of observations can be identified relatively easily, for example trough variations of experimental conditions and retesting.

As far as we know, AB-studies on HF-trading had not been published at the time of this work. Further, whereas AB-models of financial markets usually aggregate trading over days, HF-traders use to operate in seconds. This and other reasons explained next suggest developing a new model for the analysis of intraday trading.

[45] Beja and Goldman (1980) is regarded as one of the first, and still popular, financial market models. It mimics the behaviour of two agent groups (trend-followers and fundamental traders) in a very simple framework to explore their influence of price dynamics.

3.2 Model Setup

In general, the model represents a financial market in which a single stock is traded. The model agents should be imagined as algorithmic day traders, who trade several times a day and rely on a constant trading strategy executed by computers. Each agent either represents a LF- or HF-trader. At each time of decision making, a trader performs the following sequence of actions. (1) She updates her memory, i.e. her perception about relevant market variables. (2) She forms an expectation about prices (3). She submits or accepts limit orders.

Due to the properties of HF-trading and the related research questions, the model needed to fulfil several requirements. Table 1 summarizes these requirements and the model features by which they are met.

Requirement	**Corresponding model feature**
The model must account for the small time scale HFT occurs in.	Simulation runs represents days. Within a simulation run any time window, down to singular trades, can be displayed.
The implementation of differences of trading speed should be easy.	Time is continuous. Events, such as trades or fundamental news, can occur at arbitrary moments.
The trading mechanism should allow evaluating the influence of HFT on market liquidity and trading volume.	Trading is done via a bilateral order book, with market makers supplying liquidity and aggressive traders accepting orders.

Table 1: Model requirements and features.

In a detailed fashion, the model can be described as follows.

3.2.1 Time

Figure 1 illustrates the logic of the time stream. In the model, time is continuous and, like in real markets, the dynamics is driven by events. There are two kinds of events. The first one is fundamental news. The news arrival process is usually interpreted as completely random (e.g. Fama, 1970). Adopting this assumption, the temporal gap between singular news can be formalized as:

$$\Delta t_F = |N(0, \sigma_0)| \tag{1}$$

where Δt_F stands for the temporal gap between the next and the last fundamental news at time t, and this gap, which is necessarily positive, is assumed to follow a normal distribution with mean 0 and standard deviation σ.[46]

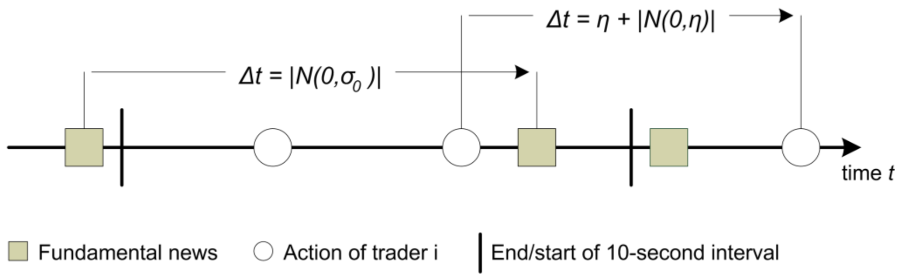

Figure 1: The concept of time in the model.

The second kind of events refers to the decisions about trading made by agents. The frequency with which the ATs make trading decision is determined by their latency, and we assume that the latency is determined by the technology the trader is endowed with. The time, Δt_D, between two moments of decision making by a specific agent i, is computed as follows:

$$\Delta t_D = \eta_g + \left|N(0, \eta_g)\right|, \tag{2}$$

where η_g is a constant positive parameter which is depended on the group g (HF or LF) trader i belongs to.[47] The first constant component can be interpreted as the time of order execution. This time is influenced by the local distance of the agent to the trading platform. HF-traders seek to locate their computers as close as possible to the server of the platform to reduce the time of data transmission. As the local distance between trader and platform is constant, we assume that transmission, and thus, execution time does not vary greatly. The second, variable component can be interpreted as the time needed for decision making. This time is influenced by the computational power used by the trader to process relevant market data and the amount of this data. As the amount of data can vary, the component is modelled as a random variable which follows a normal distribution.[48] For reasons of simplicity, we assume the standard

[46] (2) states that the time at which news occur cannot be foreseen precisely. This is not completely true for real financial markets. For example, at 13.30 GMT the Wall Streets opens, whose opening prices usually mark a significant signal for investors in Europe. Nevertheless, to keep the model simple, we abstract from such phenomena.

[47] To be precise, instead of Δt_D we should write $\Delta t_{i,t}^D$ because the value of the variable changes over traders and over time. Similarly, Δt_F should be replaced by Δt_t^F because the respective values change over time. We refrain from this notation for reasons of simplicity.

[48] The technical consequence of the random component is that the order in which traders get “on turn” is not constant but changes, which we believe to be a more realistic model behaviour.

deviation, η_g, of this variance and the constant component to be equal. The latency of trader i is thus determined uniquely by the parameter η_g.

Due to the conception of time applied, discrete steps are absent and events can occur at any moments during the day, e.g. trader i might submit an order at 14h 30m 16s. This enables the measurement of time with any precision and facilitates the implementation of trading speed, by adjusting of latency coefficient η.

3.2.2 Fundamental Value

Fundamental news occur model exogenously. As described in Section 3.2.1, news occurs at random intervals of time. The same applies for their impact on value. Whenever news arrives, the fundamental value is updated as follows:

$$F_t = F_t + \theta_t, \theta_t \sim N(0, \sigma_1), \tag{3}$$

where θ_t represents the size of the news, which follows a normal distribution with mean 0 and standard deviation σ_1.

3.2.3 Memory Updating

Being fundamental for the derivation of any trading decision, traders perceive the current behaviour of the market. This subjective perception is 'stored' in their memory. Agents update their memory at each time of decision making. With M_t being a memory variable C_t being the most recent observation of this variable, the memory updating process, $M(M_t, C_t)$, is based on a moving average:

$$M(M_{i,t}, C_t) := M_{i,t} = m\, M_{i,t} + (1-m)C_{i,t} \tag{4}$$

The equation implies agents to believe that the behaviour of prices is persistent to some degree which is determined by the 'memory parameter' m ($m \in [0;1]$). The lower m, the more weight agents give to the most recent observation compared to previous ones. There are two memory variables in the model: Price volatility $V_{i,t}$ and the mean level of prices $\hat{P}_{i,t}$.

3.2.4 Expectation Formation

To derive trading decisions, investors form expectations about the evolution of prices in their trading horizon. In our model, the trading horizon of investors is equal to the time span between two moments of decision making. To make accurate predictions about the strength of price movements over Δt_D, traders consider the historical volatility of prices over these interval. This basic principle can be written as:

$$E_{i,t}\left[\left|r_{t,t+\Delta t_D}\right|\right] = \beta_0\sqrt{\eta_g} + \beta_1\, V_{i,t}, \tag{5}$$

with

$$V_{i,t} = M\left(V_{i,t}, \left|r_{t-\Delta t_D,t}\right|\right) \tag{6}$$

Here, $E_{i,t}\left[\left|r_{t,t+\Delta t_D}\right|\right]$ is the expectation of trader i at time t about $\left|r_{t,t+\Delta t}\right|$, the absolute return from t to $t + \Delta t_D$. $V_{i,t}$ is the historical volatility as perceived by i in t, and β_0 and β_1 are positive parameters. $V_{i,t}$ is a memory variable which is computed as described in eq. (4) with $\left|r_{t-\Delta t_D,t}\right|$ being the return from i's last moment of decision making $(t - \Delta t_D)$ to t.[49]

Eq. (3) states that traders' expectation about the movement of prices is partly constant ($\beta_0\sqrt{\eta}$) and partly influenced by their experience about past price movements. Because Δt_D is determined by the trader's latency (η_g), $\left|r_{t+\Delta t_D}\right|$ is necessarily dependent on η_g, too. The first constant component accounts for this fact directly, and the second time variant one in an implicit way. To understand the first component, assume that the latency of an arbitrary agent changes by the factor k. How would this affect her expectation about $\left|r_{t+\Delta t_D}\right|$ if she is rational? To get the answer, the agent had to consider first that each change of the latency by k leads to a change of the average Δt_D, respectively $\mathrm{E}[\Delta t_D]$, by the same factor (compare eq. 1). Second, she has to derive how this affects $\left|r_{t+\Delta t_D}\right|$. Proposition 1 refers to this relation:

Proposition 1:
Assume that price changes follow an IID process and are normally distributed. Then, if Δt changes by some factor k, the absolute return over delta, $|r_{\Delta t}|$, will change by $\sqrt{k}$. Put formally:

$$|r_{k*\Delta t}| = \sqrt{k} * |r_{\Delta t}| \tag{7}$$

(Proof in appendix)

Though eq. (4), the expectation of traders about future volatility is determined by their experience about historic volatility. However, due to the constant component, agents may never expect volatility to settle down to zero, which is important for the continuation of the dynamics of prices – in the model as in reality. Interpreted differently, (4) might be regarded as a transformation of the popular (G)ARCH models on the level of agents. Just as the

[49] To be precise, we should write $\left|r_{t,t+E_{i,t}[\Delta t_D]}\right|$ because agents can only form expectations about the time of their next trading decision.

(G)ARCH models (Engle, 1982; Bollerslev, 1986), (4) is able to generate volatility clustering. However, while the G(arch) models describe the long memory process directly, in our model, the phenomenon is produced more indirectly via the expectation formation of agents.

The expectation about the absolute return is fundamental to form an expectation about the raw return, and thus, future prices. The expectation of the raw return is determined by the prediction strategy s, a specific trader relies on. Expressed formally:

$$E_{i,t}\left[P_{t+\Delta t_D}\right] = P_t + E_{s,t}\left[r_{t,t+\Delta t_D}\right], \tag{8}$$

where P_t being the price in t, and $E_{s,t}\left[r_{t+\Delta t_D}\right]$ denotes i's expectation about the raw return from t to $t + E[\Delta t_D]$ produced by strategy s.

3.2.5 Price Forecasting

Usually, successful prediction strategies are kept secret as good as possible. This applies particularly to the algorithms used by HF-traders. Nevertheless, we have some evidence about the types of strategies which are used in practice. We mimic five strategy types in a very simplified fashion: Fundamental analysis, event trading, mean-reversion, trend extrapolation and noise trading. Event trading and mean-reversion are assumed to be typical strategies used by HF-traders. In the following, the strategies are introduced in the given order.

Fundamental analysis

Fundamental analysis means the derivation of the true value of the financial security by analyses of the underlying assets (For standard volumes see Stein, 1988; Greenwald et al., 2001; and Damodaran, 2002.). Fundamental traders expect prices to return to value sooner or later. The strategy can be formalized as:

$$E_{fund,t}\left[r_{t,t+\Delta t_D}\right] = \begin{cases} +f_t & if\ \ P_t < F_t \\ -f_t & if\ \ P_t > F_t \end{cases}, \tag{9}$$

with

$$f_t = min\left\{|P_t - F_t|, E_{i,t}\left[\left|r_{t,t+\Delta t_D}\right|\right]\right\}. \tag{10}$$

F_t should be interpreted as the fundamental value of the stock in t or the price of any other security which is relevant for value (e.g. a financial derivative). The equations states that fundamentalist expect prices to move towards value, whereby the expected size of the price adaption is derived from its historic volatility. However, fundamentalists do not expect prices to over- or undershoot value (eq. 10).

Fundamental analysis is a popular strategy by long-term investors, but it is usually not used by HF-traders, because their trading horizon is much shorter than the time in which fundamental corrections are expected. Zhang (2010), for example, remarks that "HFT are agnostic to a stock's price level and have no intrinsic interest in the fate of companies, leaving little room for a firm's fundamentals to play a direct role in its trading strategies".

Event trading

Although HF-traders do not account the fundamental value directly, they do react to fundamental news – a strategy known as event trading. In theoretical research a similar class of investors has been denoted as "newswatchers" (Hong and Stein, 1999; Stein, 2009). Event trading seems also to be reflected in price dynamics. Zhang (2010) reports that "stock prices react more strongly react to news about fundamentals when HF-trading is at a high volume." The strategy can be formalized as:

$$E_{event,t}\left[r_{t,t+\Delta}\right] = \begin{cases} +v_t & if \;\; N_t - (P_t - P_{t_N}) > 0 \\ -v_t & if \;\; N_t - (P_t - P_{t_N}) < 0 \end{cases},^{50} \tag{11}$$

with

$$v_t = min\{|N_t - (P_t - P_{tN})|, E_{i,t}\left[\left|r_{t,t+\Delta t_D}\right|\right]\}, \tag{12}$$

where N_t denotes the change of the fundamental value of the stock in t caused by the latest fundamental news, and P_{t_N} is the price at the time this news arrived the market. The equations states that event traders expect prices to react accurately to the most recent change of value. For example, if the latest news increased the value of the asset by 1% but prices have risen by 0.6% only since that moment, traders expect another rise of prices equal to their volatility expectation but not greater than 0.4%. In the context of event trading we propose to interpret F_t also as an index or security whose value is relevant for the value of the asset observed. This might reflect the fact that HF-traders often seek to exploit divergences between stocks which reveal significant "short-term statistical correlations" (Zhang 2010).

Mean reversion trading

Probably one of the most popular strategies of HF-traders is mean (reversion) trading. Boogard (2010), for example, investigates data from the U.S. equities market and studies the strategies used by HF-traders. One of his key findings is that "HF-traders tend to follow a price reversal strategy driven by order imbalances." Chiu et al. (2011) shows how such a

[50] By definition, news are never 0. Hence the case $N_t = 0$, does never occur.

strategy can be implemented as a computer program and applied profitably in a real market. Mean reversion traders believe that market anomalies, i.e. significant deviances from its average behaviour, are rather the product of randomness then of systematic causes. Imagine, for example, that a large buy order enters the market, which removes enough liquidity to push the ask price to a higher level. The mean reversion traders would bet that the resulting price rise is only temporary. Hence they react by selling to take profits as the market returns to its normal level. In a very simple fashion, we formalize this behaviour as follows:

$$E_{mean,t}\left[r_{t,t+\Delta t}\right] = \begin{cases} +p_t & if \;\; P_t < \hat{P}_t \\ -p_t & if \;\; P_t > \hat{P}_t \\ 0 & otherwise \end{cases} \tag{13}$$

with

$$p_t = min\left\{\left|P_t - \hat{P}_t\right|, E_{i,t}\left[\left|r_{t,t+\Delta t_D}\right|\right]\right\} \tag{14}$$

and

$$\hat{P}_{i,t} = M\left(\hat{P}_t, P_t\right). \tag{15}$$

where $\hat{P}_{i,t}$ is the mean level of price as perceived by trader *i* in *t*, which is a memory variable.

Trend Extrapolation

Trend extrapolation represents the opposite of mean reversion in so far as with this strategy movements of prices away from its mean are not believed to revert but to continue. Accounting for this, we write:

$$E_{trend,t}\left[r_{t,t+\Delta t_D}\right] = \begin{cases} -p_t & if \;\; P_t < \hat{P}_t \\ +p_t & if \;\; P_t > \hat{P}_t \\ 0 & otherwise \end{cases} \tag{16}$$

where p_t and $\hat{P}_{i,t}$ are computed as in eq. (9) and (10). Although there is no evidence that prices follow trends in the short-term (otherwise we would observe positive correlations in returns), the idea to apply this strategy at high frequency is to imitate the behaviour of fundamental analysts. If a trend follower observes a large order to enter the market and moving prices in a certain direction, she assumes that the order stems from a fundamentalist with private information about the value of the asset. Yet, as the trading power of the fundamentalist might be too small to provoke the complete adaption of prices to its new value, other fundamental orders may follow and prices may continue to rise. The trend followers can exploit this scenario if she is fast enough to trade in the same direction before the following fundamental orders are executed. Lehalle (2010) confirm trend following behaviour in HF by observing "the smaller the horizon of the HFT, the more they will act as "market impact followers".

Noise trading

Noise traders form random predictions about future returns. However, as with all other traders, the size of their predictions is influenced positively by their perception about historic price volatility:

$$E_{noise,t}\left[r_{t,t+\Delta t}\right] = \sqrt{2/\pi} * N(0,1) * E_t\left[\left|r_{t,t+\Delta t_D}\right|\right], \tag{17}$$

where $N(0,1)$ represents a random term which follows a normal distribution with unity variance. The factor $\sqrt{2/\pi}$ is a leveling coefficient with π being the circle constant. Without $\sqrt{2/\pi}$, $\left|E_{noise,t}\left[r_{t+\Delta t_D}\right]\right|$ would on average be greater than $E_t\left[\left|r_{t+\Delta t_D}\right|\right]$ because $E[|N(0,1)|] = 1/\sqrt{2/\pi} > 1$ (Goldstein and Taleb, 2007). This would contradict to the idea that traders believe historical volatility to be the best proxy for future volatility. To preserve this principle we have assure that $E\left[\left|E_{noise,t}[r_{t+\Delta}]\right|\right] = E\left[\left|N(0,1) * E_t\left[\left|r_{t+\Delta t_D}\right|\right]\right|\right]$. Hence, we have to multiply the right side by $\sqrt{2/\pi}$.

Note that noise trading is not a prediction strategy in a strict sense. Rather, the behaviour serves as a summary for the multitude of trading strategies which are not modelled explicitly.

Market making

Market makers do not bet on a certain prediction strategy but limit themselves to the assumption that the price of today is the best proxy for the price of tomorrow. Hence:

$$E_{market}[r_{t+\Delta}] = 0, \tag{18}$$

In Section 3.2.8, the behaviour of market makers will be explained in more detail.

3.2.6 Demand Formulation

In general, investors buy if they expect prices to rise and sell if they expect a fall. This principle is restricted by two factors. First, agents have to consider the bid-ask spread. Each buy is executed at the current ask price, Ask_t, – the best price at which shares are offered. Vice versa, each sale is served at the current bid price, Bid_t – the best price at which any other trader wants to buy. (At the moment, we consider only those traders who accept orders).

Bid-ask spreads are particularly important for HF-traders since the returns over their trading horizons are usually relatively small compared to the spread.

The second factor derives from existing inventories. By analyzing high frequency data on the level of individual transactions, Kirilenko et al. (2011) report that HF-traders "actively keep inventories near a target inventory level." and "do not accumulate a significant net position and their position tends to revert to a mean of about zero." Hence, if a HF-trader receives a buying (/selling) signal but already possesses a relatively great long (/short) position, the size of her demand will be reduced. Moreover, trades might be motivated completely by a trader's desire to reduce his inventory without reacting to any trading signal. Both factors are accounted as follows.

$$B_{i,t} = B_{i,t}(Ask_t) := max[\alpha \frac{(E_{i,t}[P_{t+\Delta t}] - Ask_t)/P_t}{P_t} - \Omega, 0], \tag{19}$$

$$S_{i,t} = S_{i,t}(Bid_t) := max[\alpha \frac{(E_{i,t}[P_{t+\Delta t}] - Bid_t)/P_t}{P_t} - \Omega, 0] \tag{20}$$

with

$$\Omega = v_g * I_{i,t} * P_t, \tag{21}$$

where $B_{i,t}$ is the number of shares i wants to buy in t and $S_{i,t}$ is the number of shares she wants to sell (as shares can only be traded in unity, we round such that $B_{i,t}, S_{i,t} \in \mathbb{N}^+$). Ω represents agents' inventory control in a similar way than in Franke and Asada (2008). According to (19 – 21) traders buy more shares, the greater the expected return on the investment ($(E_{i,t}[Bid_{t+\Delta}] - Ask_t)/P_t$), the lower the price of the stock, P_t, and the lower the value of their asset inventory ($I_{i,t} * P_t$). α and v_g are constant parameters ($\alpha, v_g \geq 0$). α can be interpreted as the trading power of agents, and v_g regulates the intensity by which they seek to dispel long (/short) positions. Here and in the rest of the model, we do not distinguish between long and short trading.

3.2.7 Trading

One of the most common trading mechanisms in stock markets is the double order book (Bouchaud et al. 2002; Chiarella and Iori, 2002; Luckock, 2003; Potters and Bouchaud, 2003). Double order books allow traders either to submit limit orders – offers to buy or sell for a price equal or better as a certain limit – or to accept them. The price of the highest limit buy order is denoted as "bid", and the price of the lowest limit sell order as "ask". The term ($Ask_t - Bid_t$) is denoted as (bid-ask) spread, which is typically positive (otherwise, a limit order would have been submitted, although trading at that limit had already been possible).

The spread is an indicator for market efficiency as a lower spread reduces the cost of switching from the buy to sell side and vice versa.

The model reproduces this trading mechanism. We assume that every trader, except market makers, behave aggressively, i.e. they accept orders. Market makers act passively by submitting limit orders. For non market-makers the procedure is simple. At every turn, the trader decides if she wants to trade at the current bid or ask, i.e. Ask_t and Bid_t are inserted into (14), respectively (15). If the result is positive, the inventory of the trader is updated:

$$I_{i,t} = I_{i,t} + B_{i,t} - S_{i,t} \tag{22}$$

By accepting limit orders, the trader absorbs market liquidity, which can result in the disappearance of limit orders and a shifts of Bid_t or Ask_t. If the trader absorbs a limit order completely, she proceeds with the next best order. The trading process repeats, until there are no limit orders left that the agent wishes to accepts.

3.2.8 Market Making

Market makers (Stoll, 1978; Glosten and Milgrom, 1985; Hendershott and Seasholes, 2006) can be interpreted as liquidity providers. Therefore, we assume that these traders limit themselves to the submission of limit orders. Market maker strategies might be as diverse as the ones of aggressive traders. For example, they seek to identify large orders, which are submitted in small chunks, and to exploit them by appropriate adjustments of prices; or they try to collect premia which are paid by the trading platform for the provision of liquidity. In our model, market makers rely on their probably most straightforward behaviour: The simultaneous submission of limit orders on buy and sell side. With this strategy, market makers offer to buy shares at a lower price and offer to sell shares at a higher price. If both orders are accepted, the market maker earns the spread between bid and offer.

In the model, the strategy is implemented quite simply. For any possible price P greater P_t than (as in a real markets only discrete prices are possible), the market maker computes the number of shares he wishes to offer as follows.

$$B_{i,t}^{m}(P) = max[B_{i,t}(P) - \textstyle\sum_{(P^-)} B_{i,t}(P^-)\,, 0] \tag{23}$$

and

$$S_{i,t}^{m}(P) = max[S_{i,t}(P) - \textstyle\sum_{(P^+)} S_{i,t}(P^+)\,, 0] \tag{24}$$

Here, $B_{i,t}^{m}(P)$ stands for the number of limit buy orders the market maker i submits at price P and $S_{i,t}^{m}$ for the respective sales. P^- denotes some possible price smaller than P and P+ some price greater. $B_{i,t}(\mathrm{P})$ and $S_{i,t}(P)$ are the same demand functions as used by all other traders. To understand the mechanism, assume that $P_t = 34.40$ when market maker i is going to make her trading decision. Depending on the institutional regulations in the market, i can make offers only at discrete prices. Assume that the next higher prices for which this is possible is 34.405. As a market maker, i does not assume that prices will change. Thus, if he would place an offer at 34.405, she would expect a relative profit of $(34.405 - 34.40)/34.40$ if the order is accepted. The demand function (19) yields the corresponding demand for this profit which is equal to the number of limit sell orders i submits. The next greater price for which i can offer shares is 34.410. Again, i computes the expected profit and the corresponding demand. However, this time she needs take into account that any trader who would accept an offer at 34.410 would accept the offers at 34.405 at first. Hence, the number of sell orders submitted by i at 34.405, respectively any lower price, have to be subtracted. The logic is repeated for any greater price P, and applied vice versa for the submission of bids.

3.2.9 Price

Finally, the trading by the agents determines the evolution of prices. We have already commented on some aspects of prices but others have been ignored so far.

As a general principle, every monetary variable, P, F, Bid and Ask, can only assume discrete variables. We will adopt the set of possible values from a real market, which is described in Section 5, and round the monetary variables in the model accordingly. Another important fact relates to the interpretation of prices. Whereas in the long frequency world, the current price P_t is often defined as the price for which the last trade was executed, in a high frequency world, it is usually computed as the mid between bid and ask. One of the reasons is that, if considering the prices at which trades are executed, microstructure effects come into play; P_t would fluctuate between bid and ask which would lead to unwanted effects for indicators of price dynamics, such as volatility, over small observation intervals.

3.3 The Base Configuration

Our study aims at exploring how different strategies affect financial dynamics, either if they are used in low frequency or in high frequency. Traders who use a particular strategy at a particular frequency should be regarded as a group of traders. To isolate the effects of these groups on the market dynamics, we proceed as follows: In a base configuration only market makers, noise traders and fundamentalists are active. All traders act in low frequency. This model is fitted to the real data. In a second steps, the other groups of traders are induced one after the other. Comparisons of the values of relevant indicator in these scenarios to the base configuration yield insights of the effects speeds and strategies.

The base configuration implies a rather simplistic interpretation of the real market. This interpretation is based on a large body of empirical evidence according to which traders can be distinguished into two major groups (Taylor and Allen, 1992; Menkhoff, 1997; Lui and Mole, 1998): Fundamentalists, who seek to identify mispricing, and chartists, who use technical rules of trading.[51] Since the variety of technical rules is very large, the behaviour of chartists as a group can be approximated as noise trading. Agent-based financial market models often adopt the distinction between technical and fundamental traders by following the 'fundamentalist-chartist' approach.

It might be argued that a more adequate approach would be to include the other groups of traders in the base configuration already. This, however, would require reliable information about the share of each group in the market. Since traders use to keep their strategies secret, this information is not available yet. Hence, a bunch of assumptions about the share of each group would need to be made, and the isolation of the effect of each group would be acerbated.

4. INDICATORS OF FINANCIAL MARKET DYNAMICS

In our study, we use two indicators of market dynamics which require a closer definition and interpretation – the Hill-tail index and the Hurst coefficient. The indicators are needed in the context of model validation and to evaluate the simulation experiments.

4.1 Hill-Tail Index

The tail index of the return distribution reflects the proportion of returns in the tails of the distribution. A high value of the index points to a great likelihood of extreme returns and, thus, great risks for investors. The market can be regarded as more efficient and less governed by stress if the tail index is small. The Hill estimator H (Lux and Ausloos, 2002), gives an approximation of this index. It is defined as follows:

$$H = \left(\frac{1}{I}\sum_{i=1}^{I}(ln|\Delta p_{L-i+1}| - ln|\Delta p_{L-I}|)\right)^{-1} \qquad (25)$$

[51] For standard volumes on fundamental analysis see Stein, 1988; Greenwald et al., 2001; and Damodaran, 2002. Volumes on technical trading include Murphy, 1999; Pring, 2002; and Edwards et al., 2007.

where k denotes the number of observations in the tail. To calculate the index, the returns Δp_t have to be sorted in a descending order: $\Delta p_L > \Delta p_{L-1} > \Delta p_{L-2} > \dots > \Delta p_1$. Common tail fraction are 3% and 5%.

4.2 Hurst Coefficient

The Hurst coefficient (Hurst, 1951; Mandelbrot and Van Ness, 1968; Mandelbrot, 1982), H ($H \in]0;1[$), captures the tendency of a time series to show long memory. Long memory, i.e. positive long-term autocorrelations, corresponds to a Hurst exponent of $0.5 < H < 1$. In other words, a high (/low) observation tends to be followed by another high (/low) observation. This behaviour can also be interpreted as volatility clustering. A Hurst exponent of $0 < H < 0.5$ points to a time series in which high and low observations alter with each other. For a random series, the Hurst coefficient tends to be 0.5. Originally used to describe the statistical properties of floods in the Nile delta, the Hurst coefficient has been transferred to the field of financial research (May, 1999; Corazza and Malliaris, 2002), for example, in the context of forecasting (Grech and Mazur, 2004; Qian and Rasheed, 2004). When taking the Hurst coefficient for the absolute returns of a financial time series, the results usually exceeds 0.5 (Qian and Rasheed, 2004; Smith, 2010), which confirms the stylized facts, long memory and volatility clustering. For a time series, $X = X_1, X_2, \dots, X_{\mathrm{N}}$, the Hurst coefficient can be calculated by as follows:

(1) Calculate the mean value m:

$$m = \frac{1}{n}\sum_{i=1}^{n} X_i$$

(2) Calculate the mean adjusted series Y:

$$Y_t = X_t - m, \qquad t = 1,2,\dots,n$$

(3) Calculate the cumulative deviation series Z:

$$Z_t = \sum_{i=1}^{t} Y_i, \qquad t = 1,2,\dots,n$$

(4) Calculate the range series R

$$R_t = \max(Z_1, Z_2, \dots, Z_t) - min(Z_1, Z_2, \dots, Z_t), \qquad t = 1,2,\dots,n$$

(5) Calculate the standard deviation series S

$$S_t = \sqrt{\frac{1}{t}\sum_{i=1}^{t}(X_i - u)^2}, \qquad t = 1,2,\dots,n,$$

with $u = \frac{1}{t}\sum_{i=1}^{t} X_i$.

(6) Calculate the rescaled range series (R/S)

$$(R/S)_t = (R_t/S_t), \qquad t = 1,2,\dots,n$$

Hurst found that (R/S) follows a power-law as time increases:

$$(R/S)_t = c * t^H,$$

where c is a constant and *H* represents Hurst coefficient (see Qian and Rasheed, 2004). To approximate *H*, (R/S) is plotted versus *t* in log-log axes. The slope of the regression line gives an estimate for *H*. For t, it is common to use integer powers of 2. In our experiments, simulation runs are divided into 2.700 time steps, which leads to a maximum of $t = 2^{11}$. For $t < 10$, $(R/S)_t$ is not accurate, which gives a minimum of $t = 2^4$. As a result, the regression is done with $(R/S)_t$ values for $t = 2^4, 2^5, \dots, 2^{11}$.

5. MODEL VALIDATION

The validation of the model comprises three aspects:

(1) The qualitative validation of the model dynamics. Here, we check if the model replicates certain stylized facts of the behaviour of the real market.

(2) The quantitative validation of the model dynamics. Here, we compare measures of several dynamic indicators.

(3) The qualitative validation of the behaviour of HF-traders. Accounting for some of the most important facts about the behaviour of HF-traders, we check if these facts are fulfilled for HF-traders in the model.

The real market is represented by the Lloyds plc equity. This security has been one of the most traded equities on the LSE at the time of data gathering, hence, a relatively large set of intraday data can be recorded. The data set comprises the 100 trading days, from 27.06.2011 to 14.11.2011, which represented the most recent period.[52] For each day we aggregated data over 10-second intervals. This length seems to be appropriate because (1) it is short enough to lead to a sufficiently high number of intraday observations and to account for high frequency phenomena and (2) it is long enough to assure that some trading action can be observed within. Regular trading at the LSE starts at 9am and ends at 16.30, which gives 7.30 hours or

[52] Source of raw data: Bloomberg. Own data processing.

2700 10-second intervals.[53] For the model validation, we conducted 1000 runs, each of them representing one day of trading with a length of 7.30 hours.

5.1 Calibration

The parameters have been chosen to match several indicators of the dynamics of that equity as good as possible. In general, the fitting of the model has been done in an explorative way, because the influence of most parameters on the model dynamics is complex. However, there are some parameters which are closely linked to one particular indicator of market dynamics. For example, the trading power of agents, α, has a direct effect on total trading volume over one day (doubling α, doubles the trading volume). Identifying these relationships may reduce the complexity of the fitting process and enables to match certain indicators of the real dynamics very accurately. Table 2 summarizes the parameters of the model, their interpretation and the dynamics indicators they are linked to.

5.2 Macro Behaviour

Figure 2 compares one typical day of trading in the model (left column) and in the real market (right column). From top to bottom the panels display: the price and value (the latter is depicted only for the model); the price returns; trading volume in terms of value; and the bid-ask spread (at the end of the 10-sec interval). Finally, the bottom panel depicts auto-correlations of raw returns (red), absolute returns (blue), and returns to the power of 2 (orange) for different lags. The gray lines indicate the 1-percent quantile of significance.

[53] Of course, trading of the Lloyds plc is not only at this time but can be done for 24 hours at other exchange market or via brokers. However, we refrain to the trading at the LSE to assure that institutional environment is constant.

Parameter	Interpretation	Dynamic indicator	Value
β_0	Basic volatility expectation	Measures of price dynamics	$1.376 * 10^{-6}$
β_1	Historic volatility orientation	Measures of price dynamics	0.3
$v_{LF,mm}$	Inventory coefficient of LF-market makers	Average holding time of HF-traders	$1 * 10^{-5}$
$v_{LF,\neg mm}$	Inventory coefficient of aggressive LF-traders		0
v_{HF}	Inventory coefficient of HF-traders	Average holding time of HF-traders	$5 * 10^{-3}$
α	Trading power	Total trading volume	$6 * 10^{6}$
σ_0	SD of time gap between fundamental news.	Daily return	30s
σ_1	SD of size of fundamental news	Daily return	$8 * 10^{-4}$
η_{HF}	Latency of HF-traders		20s
η_{LF}	Latency of LF-traders		2m
m	weight of memory	Measures of price dynamics	0.56

Table 2: Model parameters, interpretation, dynamic indicators the parameters are directly linked to and parameter value. Agents in the base configuration: 70 LF-market makers, 16 LF-fundamentalists, 154 LF-noise traders.

The figure shows that the model mimics some of the most important stylized facts of the high-frequency dynamics of financial markets. These facts are:

- Absence of autocorrelations in raw returns (Taylor, 2005): The price dynamics does not reveal any predictable pattern so that no significant autocorrelation in returns arise (see bottom panel, red graph).
- Volatility clustering (Taylor, 2005; Pacurar, 2008): Intervals of turbulence alternate with intervals in which prices evolve calmly (see return panels).

- Heavy tails in returns (Taylor, 2005): The proportion of extreme returns is significantly greater than under a normal distribution with the same mean and the same standard deviation. (We will verify this fact by computing tail indices).
- Excessive volatility (surveys by Fama, 1981, 1998, and Cochrane, 1991): Prices are more volatile than the intrinsic value of the asset. (in simulation run displayed, the average 10-second return for prices is 0.065% whereas for value it is 0.025%. The same can be observed for most other simulation days.)
- Bubbles and crashed (Kirilenko et al., 2011; Easley et al., 2010): Prices disconnect from value for significant spans of time (see top left panel). Take the flash crash as a prominent example.

Moreover, we can observe that the model behaves similar to the real market with respect to some other properties. At some times of the day, we observe massive trading volume and extreme bid-ask spreads, in the model as well as in the real market. This may point to the fact that extremely large orders enter the marker or trading is driven by some power law.

Following to the qualitative validation, we test the quantitatively fit of the model. Eight dynamic indicators are used for this purpose. Five of them capture the dynamics of prices: the average return over intervals of 10 seconds as a measure of intraday volatility; the total return over one day; the Hill-tail indices of the 10-second return distribution with tail fraction of 3% and 5%; and the Hurst coefficient for the 10-second return distribution. Three indicators relate to aspects of market infrastructure and trading: the total number of trades; the total trading volume in £; and the average bid-ask spread. Figure 3 depicts the distribution of the respective indicators for the model (blue columns) and for the real market (red line). The mean of the respective distribution is marked by a dot and the median by a dashed line. The number in the upper right corner represents the percentage to which the model distribution covers the real distribution. It can be used as an indicator for the matching accuracy.[54]

[54] We recommend not to over-interpreted this number. On the one hand the number is sensitive to changes in the number of histogram bars. On the other hand, unless the number of observations tends to infinity, divergences between the model and the real distribution might be due to chance. Hence, the indicator would be below 100% even if both samples would be drawn from the same population.

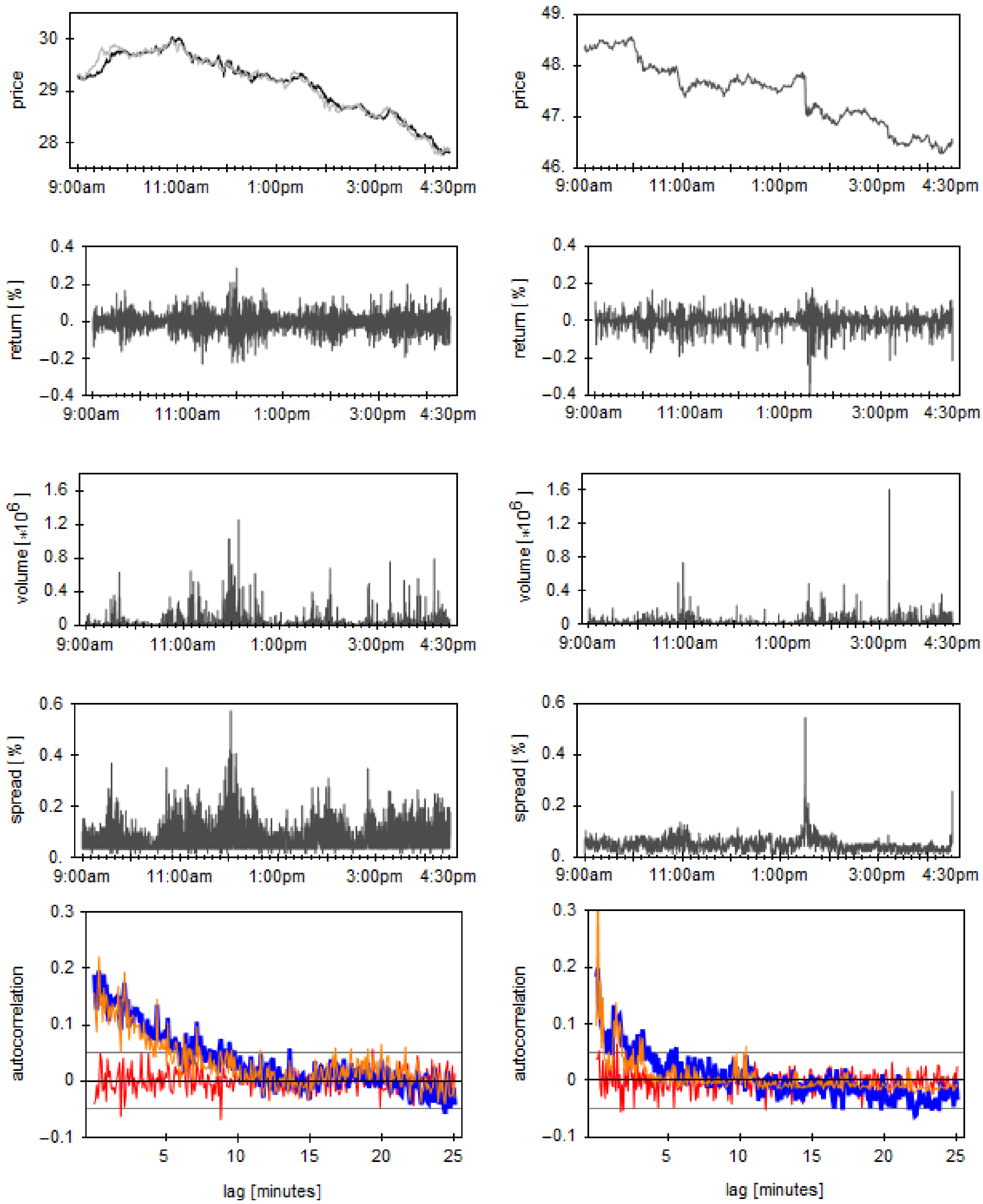

Figure 2: Simulation run vs. real trading day. Upper left panel: Price (solid) and value (grey). Bottom panels: Autocorrelation of absolute returns (blue bold), squared returns (orange) and raw returns (red).

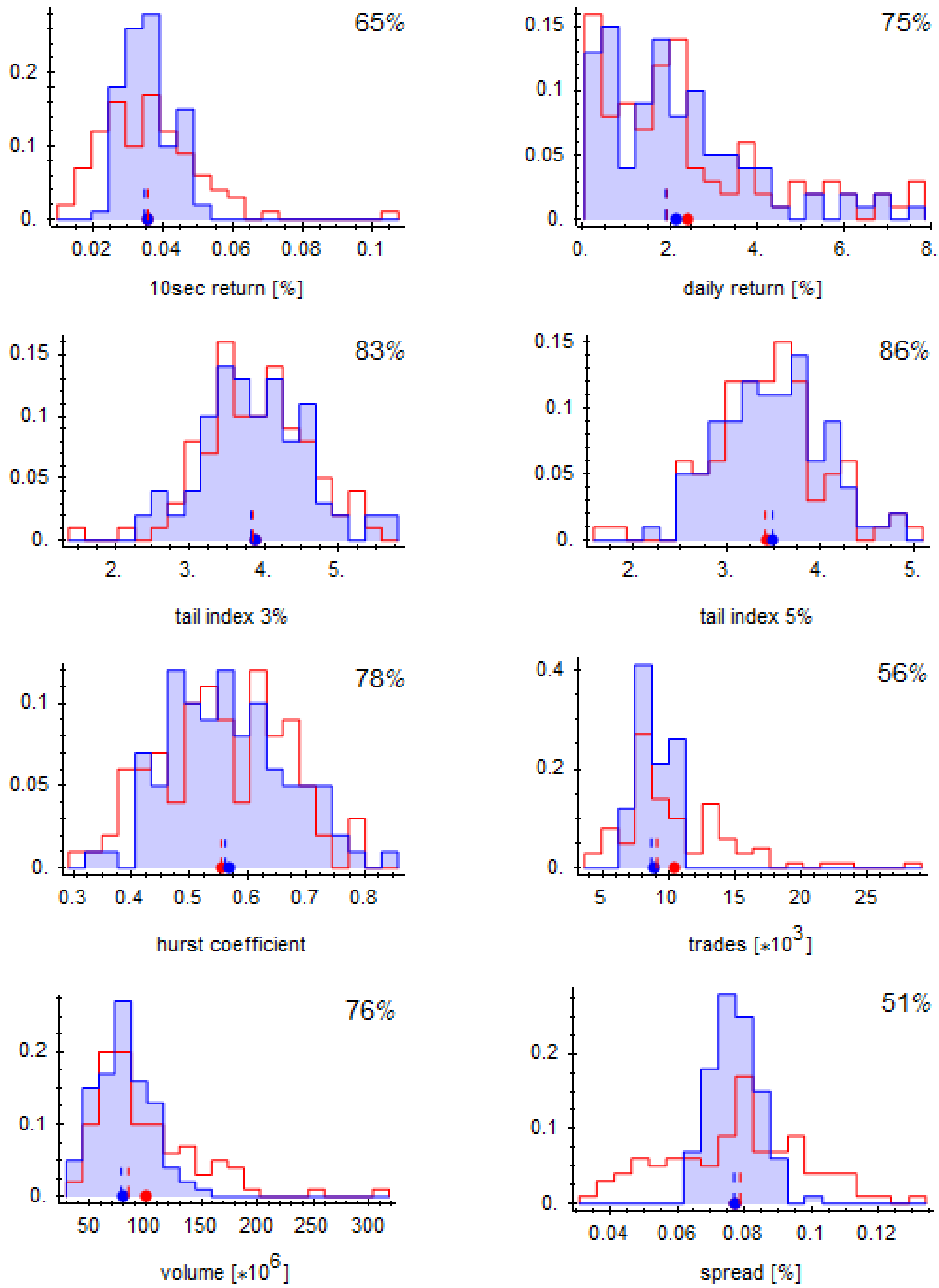

Figure 3: Quantitative validation. Blue distribution: 1.000 simulation runs of the model. Red line: 100 trading days of the Lloyds plc equity on LSE from 27.06.2011 to 14.11.2011. Values in upper right corners: percentage to which the simulated distributions cover the real ones.

It can be seen that the fit is quite accurate for the indicators of price dynamics. Only for the 10-second returns, the real market seems to reveal a greater variance than the model, which might be due to the fact that at some days there was profound insecurity about fundamental developments in the economy and the banking business – a factor which the model does not account for. This might also explain the relatively great variance of the distribution of trades, trading volume, and average bid-ask spreads in the real market. If due to an ambiguous economic situation, the expectations of traders are very heterogeneous, there is much potential for trading. This drives up the number of trades and trading volume. At the same time, bid-ask spreads rise as marker maker face high information risks, and thus behave rather observantly. Overall we believe the model to fit the real market quite well.

5.3 Micro Behaviour

As HF-traders are in the centre of this study, their behaviour requires to be validated separately. Basically, the behaviour of HF-traders is characterized by three stylized facts compared to LF-traders:

(1) By definition, HF-traders trade significantly more often than LF-traders. However, they trade still much less often than their technical capabilities would allow (Boogard, 2010).
(2) The volume of transactions and net positions (Kirilenko et al., 2011) are significantly lower.
(3) Holding times are significantly shorter. Studies report that HF-traders hold their positions only for a couple of minutes (Kirilenko et al., 2011). This aspect will turn out to be of crucial importance for the effect of HF-trading on market dynamics.

Figure 4 verifies that these HF-traders in the model comply with these facts. The figure summarizes the simulation runs in terms of box-whisker plots. The upper (/bottom) whisker represent the 95% (/5%) percentile of the distribution, the upper (/bottom) end of the boxes indicate the 75% (/25%) percentile. The horizontal line inside the box stand for the median while the mean is represented by a dot. The key for the labels is given in the caption. Plots belonging to LF (/HF) groups are coloured in blue (/red). This interpretation of the box-whisker plots is kept up throughout the study.

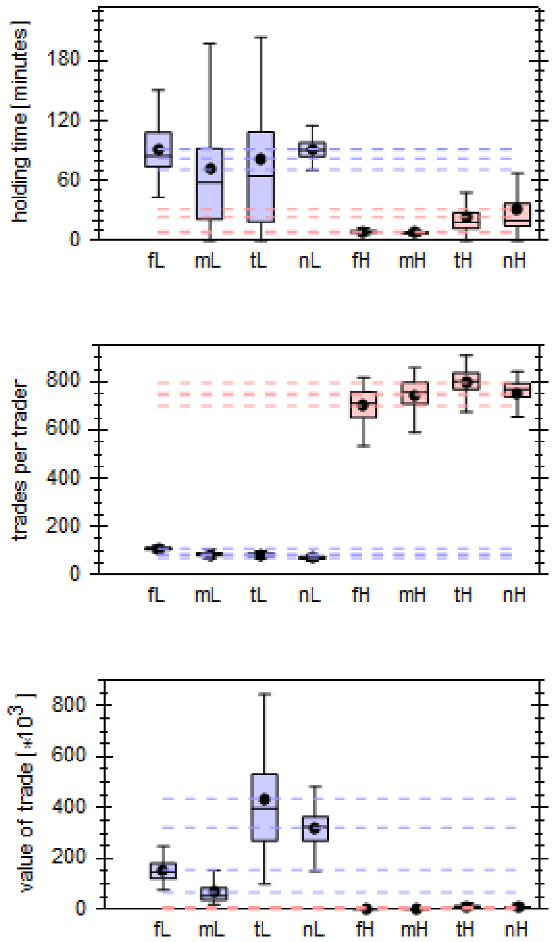

Figure 4: Micro Facts. Interpretation of box-whisker plots: Upper (/lower) whisker –95% (/5%) percentile. Upper (/lower) end of box – 75% (/25%) percentile. Vertical line inside box – median. Dot – mean. Key for labels: *f* – fundamental analysis / event trading (for HF-traders); *m* – mean reversion; *t* – trend extrapolation; *n* – noise trading. *L* – low frequency; *H* – high frequency.

6. Simulation Experiments

The simulation experiments are divided into three parts. The impact of the aggressive, respectively passive, strategies is tested in part 1, respectively 2. In part 3, we seek to give answers on those conjectures on HF-trading, which have not been tackled before.

6.1 Aggressive Strategies

In the simulation experiments, we compare different scenarios which are configured as follows. In each scenario the base configuration is extended by one additional group of aggressive traders which has not been part of the base configuration. A group is specified by a particular aggressive strategy and a particular latency. Figure 5 shows the results of the simulation experiments. The plots corresponding to the base configuration are denoted as ‘base’. The key of the abbreviations, and the scheme of the Box-Whisker plots, is the same as in figure 4. To capture the effects of market efficiency and trading, eight indicators are used.

Most of these indicator are already known from the quantitative validation of the model presented in Section 5.1. Two indicators are new: adaption time and distortion. Adaption time denotes the time between two moments in which the dynamics of prices and the fundamental value cross each other or are equal. This interval can be read as a measurement of the tendency of prices to adapt to changes of value. Distortion refers to the mean absolute difference between price and value.

As a first insight, we observe that intraday volatility rises, if trend followers are induced (top row, left panel). Furthermore, the distortion in the market is enhanced (third row, right). This applies for both, the LF-trading and the HF-trading group. The insight that trend-followers deteriorate market efficiency is already well-known (see Beja and Goldman, 1980, and followers). Trend followers exacerbate price movements by trading on them. In this way, they tend to drive prices away from value. In our model, the greater volatility of prices feeds back to the volatility expectations of traders. As traders observe greater volatility, they expect greater price movements in the future. If returns are expected to be greater, losses due to the bid-ask become less weighty. As a result, traders expect more transactions to be profitable. This disembogues into a rise of the trading volume (bottom, left). As trend followers are aggressive traders, the liquidity of the market decreases and the bid-ask spread growths (bottom row, right). Furthermore, we observe trend-following to produce a decrease of the tail-index of the return distribution (second row, left and right). In other words, the share of extreme returns rises. This is due to the fact that trend-followers induce positive feedback in the dynamics of prices. As a result, the power-law shape of the return distribution becomes more pronounced.

Mean traders behave contrarily to trend followers as they bet on price movements to revert. This behaviour tends to dampen price movements. This leads to a lower result for intraday volatility (top row, left). As traders expect lower volatility in the future, fewer transactions are expected to be profitable and trading volume declines (bottom, left). The lower absorption of liquidity, finally leads to a reduction of the bid-ask spread (bottom, right). We can conclude that trend followers tend to destabilize the dynamics of prices. In contrast, mean traders stabilize the dynamics; however they tend to detain prices from adjusting to value (third row, left).

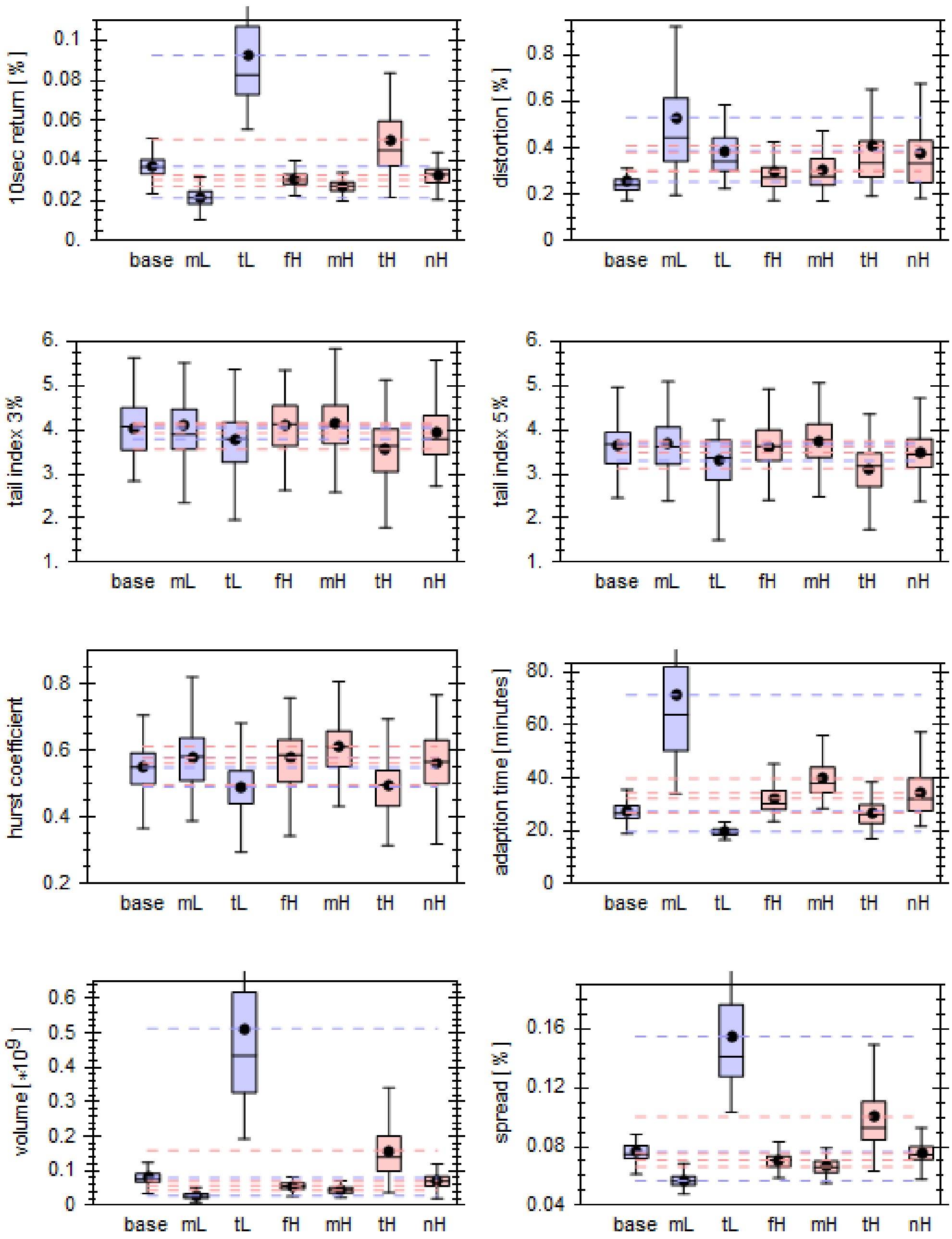

Figure 5: Market efficiency – same number. Indicators of market efficiency for the base configuration and six scenarios in which the base configuration is extended by 10 traders of a particular group. For key of abbreviations see figure 4.

In contrast to the results for mean-reversion traders and trend-followers, the results for noise traders and event-traders are less significant. The effects of high frequency noise traders on adaption time and market distortion constitute exceptions. Since noise traders do not account for the fundamental value, they tend to increase both indicators (third row, left and right).

A very important observation can be made with respect to the dimension of the effects established. Apart from the tail index, the effects are more pronounced if the respective strategy is used by low frequency than by high frequency traders. This finding becomes more astonishing by considering the degree to which the different groups participate in trading. Figure 6 illustrates the share of the total trading volume for each group. The plots show that HF-trend followers and HF-noise traders have a significantly greater share of trading than the respective LF-groups. We can conclude that HF-trend followers have a relatively little effect of price dynamics although their participation in trading is relatively great.

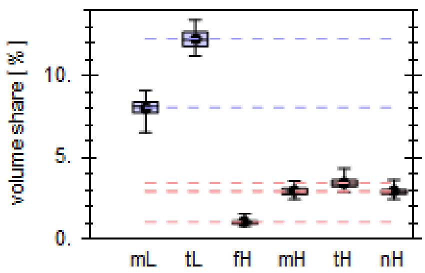

Figure 6: Trading shares. The share of each trader group of the value of the total trading volume in the market. For key of abbreviations see figure 4.

To control for differences in trading shares, we conduct a second series of experiments. This time, we induce as many traders of the different groups as needed to get approximately equal shares in trading (here: about 5%). The results are displayed by figure 7. This time, the difference in the size of the effect of HF-groups and respective LF-groups is even more pronounced. Whereas the LF-groups produce significant changes of several indicators, the influence of the respective HF-traders is very slight.

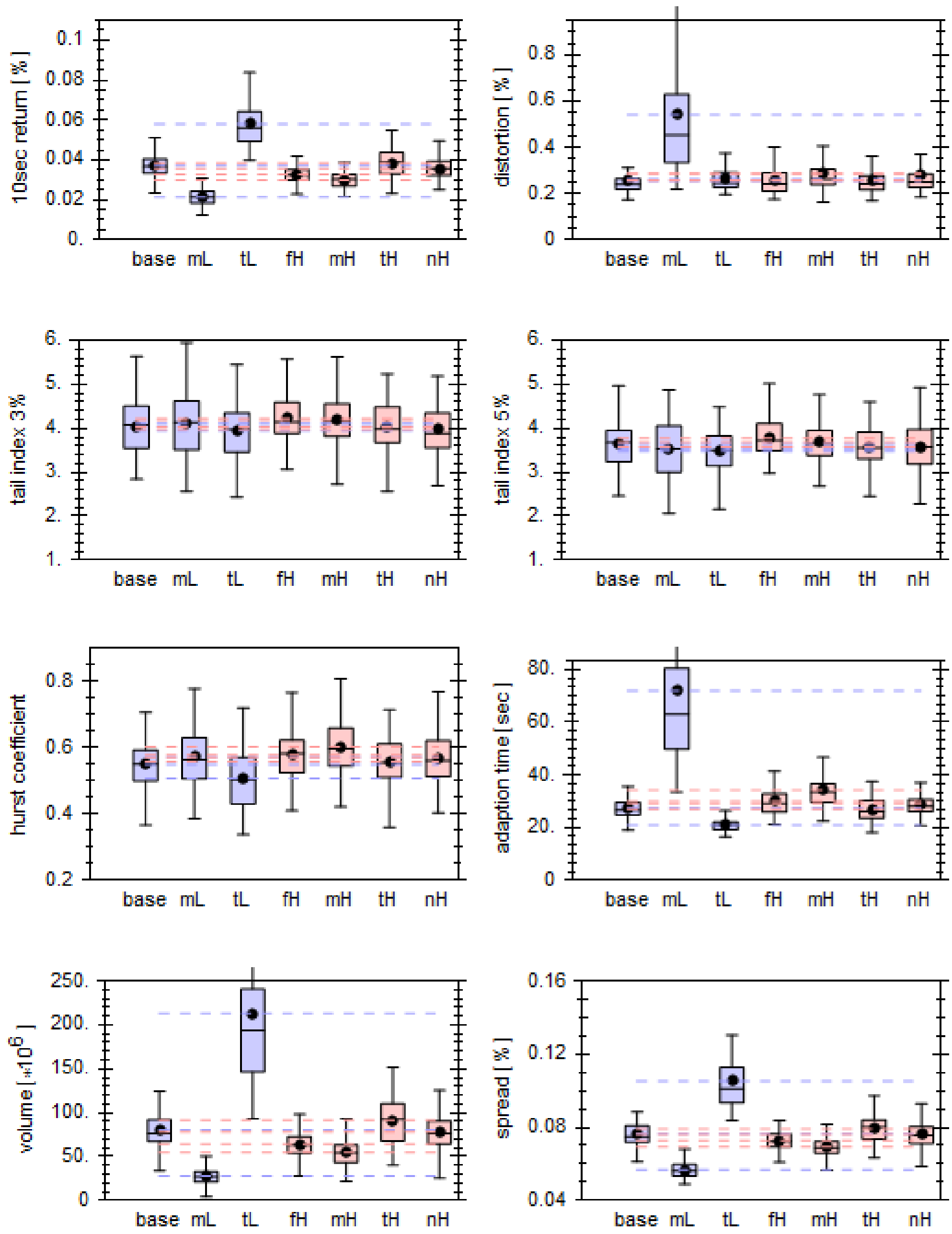

Figure 7: Market efficiency – same volume. The same as in figure 5 but this time the number of traders of the additional groups is as high as needed to produce approximately the same the trading volume from each of these groups. For key of abbreviations see figure 4.

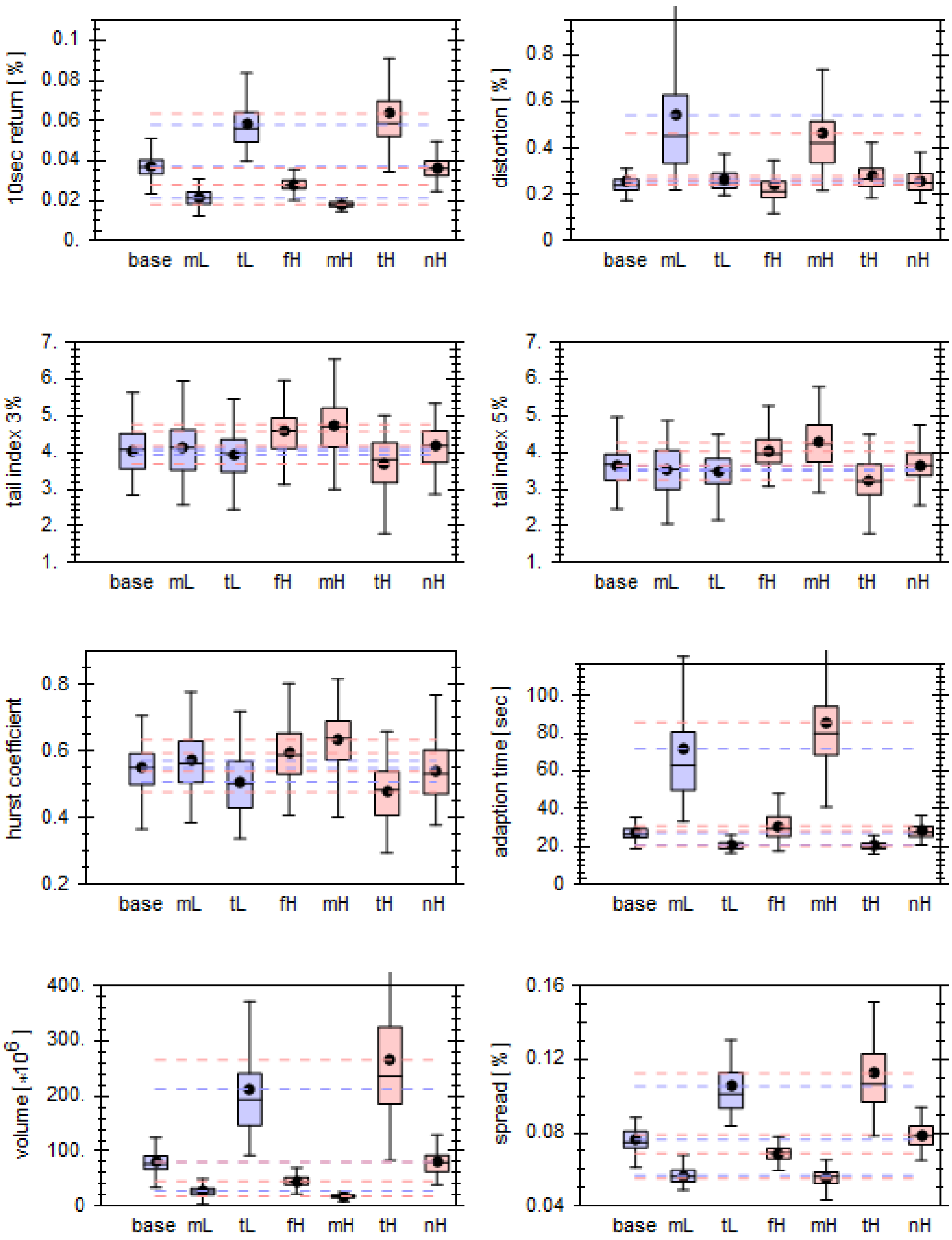

Figure 8: Market efficiency – same volume, same inventory control. The same as in figure 7 but this time the inventory coefficient of HF-traders is set equal to the one of LF-traders ($\boldsymbol{v_{HFT} = v_{LFT,\neg mm}}$). For key of abbreviations see figure 4.

The difference between the influence of HF- and LF-groups can only be due to those parameters which discriminate between these groups. These properties are (i) the latency of traders (η_g) and the degree of inventory control (v_g). The following experiment will turn out that the crucial parameter is inventory control, while the role of speed is relatively humble. This finding can be gained by annihilating the difference in inventory control between HF- and LF-traders. This is achieved by setting v_{HFT} equal to $v_{LFT,\neg mm}$. In other words, we construct a hypothetic scenario in which HF-traders do not adhere to a stricter inventory control than other traders. Figure 8 displays the results.

This time, most effects of the HF-groups seem to be equal or slightly greater than the effects of the respectively LF-groups. In sum, we cannot detect significant differences between the effects of LF- and HF-groups anymore. This observation indicates that the strong inventory control of HF-traders reduces their effects for the dynamics of prices. We believe the explanation for this finding to be quite simple. To achieve low holding times, any long or short positions that has been build up, needs to be liquidated short time later. This implies that HF-trading need to reverse any transaction quickly. For example, if they have bought in one moment, they are going to sell some seconds or minutes later. The reversion of transactions tends to level out the impetus induced by the original transaction. In this way, due to their rigorous inventory control, aggressive HF-traders tend to annihilate their impacts on the price dynamics quickly and autonomously. As a result, their effect for the dynamics of prices is relatively low.

6.2 Passive Strategies

The simulation experiments with passive strategies aim at the following question: How will market dynamics change if market making increasingly congregates around HF-traders? To answer this question, we replace the LF-market makers of the base configuration successively by HF-market makers. In the first scenario, 50% of market makers start to act in high frequency. In the second scenario, market making is conducted completely by HF-traders. HF-market makers are able to supply liquidity more often and are quicker to react to moments in which profit opportunities are great. Figure 9 illustrates the simulation results. The two scenarios with 50% and 100% HF-traders are marked accordingly. The indicators are the same as before.

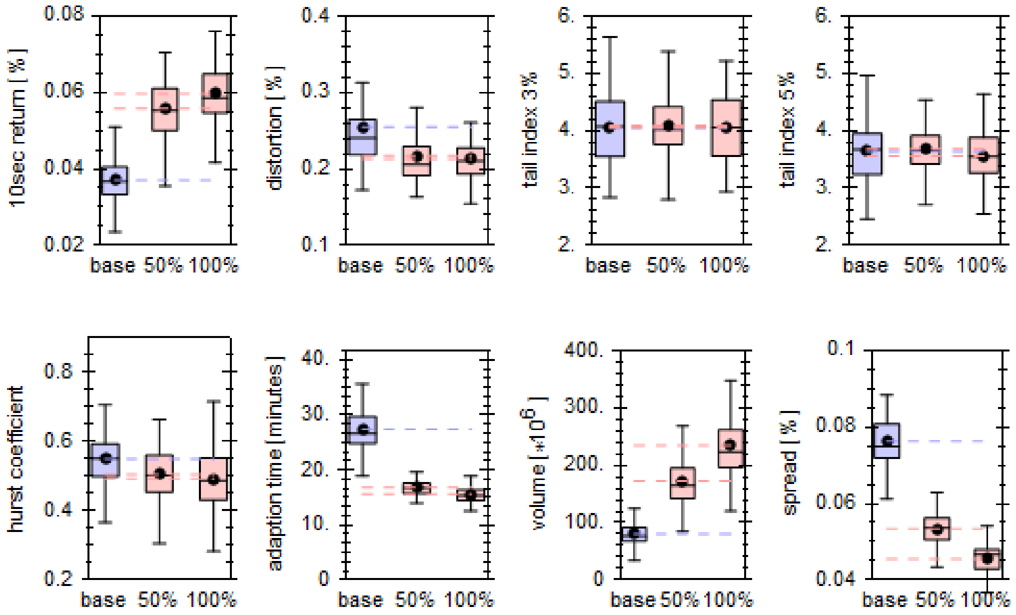

Figure 9: Market makers – same number: market efficiency. The base configuration and scenarios is which 50% or 100% of market makers have switched to HF-trading.

The results for market efficiency are relatively complex. The more market making congregates around HF-traders, the more intraday volatility rises (top row, left). On the other hand, adaption times and market distortion and tend to fall (third row, left and right). We assume the explanation to be as follows. If market makers trade with relatively high latency, they will be slow to react to times in which aggressive traders absorb many orders from the book. As a result, the bid-ask spread may rise significantly before a market maker supplies new liquidity. HF-market makers provide liquidity more often and are quicker to react to times of high spreads. As a consequence, the average spread becomes lower, the more market makers switch to high frequency (bottom, right). If spreads are lower, traders will expect more transactions to be profitable. As a result, the trading volume rises (bottom, left). We believe that the rise in volatility is due to the rise in technical intraday trading. In the model, the fundamental strategy cannot cause excessive volatility since, by eq. 9, fundamentalist expect changes of prices to be equal or lower to changes of value. Hence, fundamental transaction alone cannot cause a rise in volatility but would simply lead to the readjustment of prices and value. In contrast, technical transactions, such as trend followers tend to cause excessive movements of prices without fundamental reason. The interplay of technical traders, who drive prices away from value, and fundamental traders, who cause readjustments, leads to fluctuation of prices around value. Lower spreads catalyze the interplay between both groups of traders and, thus, the fluctuations of prices. As a result, intraday volatility rises. On the other hand, since fundamentalists expect more transactions to be profitable, more transactions are made which drive prices towards fundamentals. As a result, adaption times and market distortion decrease. In other words, due to lower spreads, the price dynamics is compressed into lower intervals of time.

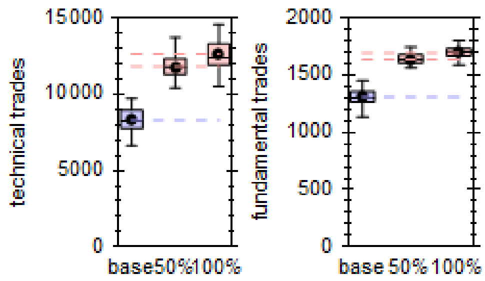

Figure 10: Technical and fundamental transactions. The numbers of transactions by technical traders and by fundamentalists when market makers successively switch to HF-trading.

Figure 10 aims at supporting the argument by displaying the number of trades by technical and fundamental traders. Both numbers rise, if market makers congregate around HF-traders. However, the increase in technical trades is relatively stronger. This indicates that, by causing lower spreads, market makers facilitate technical trading primarily. As the technical traders drive prices away from value, they create profit opportunities for fundamentalists. As a result, the number of fundamental trades rises as well and prices are forced to readjust to value.

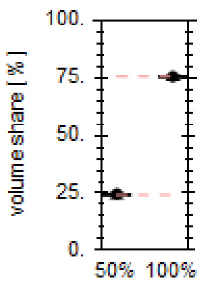

Figure 11: Market makers – same number: volume share. The share of the value of total trading volume of LF- and HF-market makers.

It might be argued that the results presented so far are sensitive to the fact that HFT market makers provide more liquidity than their LF-rivals simply because they trade more often. This might be not realistic as it implies HF-market makers to have relatively greater turnovers. Figure 11 illustrates this aspect for the scenario in which 50% of market makers are HF-traders. Although the numbers of LF- and HF-agents are equal, HF-market makers participate in about 75% of transactions and LF-market makers only in 25%. Future work is needed to isolate the effect of speed from the effect of greater liquidity provision.

6.3 Other Results

In the introduction several conjectures about the influence of HFT on financial markets have been presented. The simulation experiments presented so far could already give insights on some of these questions, whereas others have not been tackled. In the following, we want to explore the remaining questions.

As mentioned before, some authorities in financial markets suppose market making to increasingly congregate around HF-traders. We can assume that this supposition will be true if HF-market makers gain superior profits towards their LF-rivals. Figure 12 gives information about this. The figure shows the average profits per day of LF- (*mmL*) and HF-market makers (*mmH*) either per trader (left panel) or per trade (right panel).

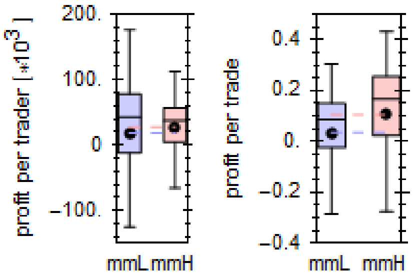

Figure 12: Market makers – profits.

The average daily profit of market makers when LF- and HF- market makers provide the same amount of liquidity. The experiments confirm HF-market makers to have an advantage in profits. This advantage is notable especially in terms of profits per trade. This indicates that the greater profit of HF-traders is not due to a greater turnover but due to their advantage in speed. HF-traders are more likely to react to moments in which bid-ask spreads are large. If in this situation, a market maker gives orders into the book, she reduces the spread instantly. However, the liquidity at the beginning of the book, which is constituted by the orders the market maker has just submitted, is still very thin. If in the next moment, an aggressive trader decides to trade, she will accept the orders at the beginning of the book at first. However, as these orders are quickly exhausted, she will also need to accept orders at relatively unfavourable conditions. For the HF-market maker, who has submitted these orders, these conditions are relatively favourable. As a result, her profits tend to be great. These observations support the original conjecture. The model suggests that market making will increasingly be in hands of HF-traders.

Another conjecture has been that HF-traders would produce an increase in the correlation between stocks. To test this conjecture in the model is difficult in so far as the model replicates the market of a singly asset only. Nevertheless, as mentioned before, it is possible to interpret the fundamental value as the value of another asset which is related to the asset focused. Hence, measuring the correlation between the dynamics of prices and the dynamics of value may give an idea about the conjecture. Figure 13 illustrates this measure when inducing the different groups of traders.

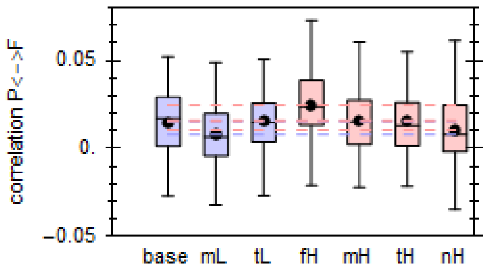

Figure 13: Correlation between stocks. The correlation between 10-second returns of prices and of the fundamental value. For key of abbreviations see figure 4.

The simulations show the answer to be sensitive to the strategy HF-traders use. If HF-traders use trend extrapolation or mean reversion, we cannot detect a significant change in comparison to the base case. If HF-traders act as noise traders, the correlation declines, because noise trading reduces the tendency of prices to follow value. The only scenario, in which the correlation rises, is when HF-traders are event traders. We think that this finding is not very surprising. By definition, event traders trade on changes of value. As a result, the tendency of price to react to the value indicator is increased and the correlation between both variables rises. The other groups of HF-traders do not account for the fundamental value. Thus, they do not have a positive effect for the correlation between assets.

The last conjecture that should be tested is if HF-traders undermine the attractiveness of fundamental trading. To this end, we measure how the profits of fundamentalists are affected by inducing the different groups of traders. The results are depicted by figure 14.

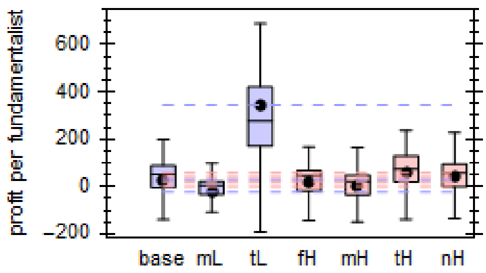

Figure 14: Profits of fundamentalists. Average daily profits of fundamentalists for the base case and when the base case is extended by other groups of traders. For key of abbreviations see figure 4.

The simulations show that fundamental profits decrease slightly if HF-traders rely on the mean-reversion strategy. However, the same observation can be made for mean reversion in low frequency. In conclusion, not traders' latency but the strategy itself deteriorates the profits of fundamentalists. To understand the reason, recall that mean-reversion trading tends to impede prices to adapt to value (see figure 5). This is harmful for fundamentalists who bet on price corrections. In contrast, fundamentalists' profits rise if trend-followers are induced. Recall that trend-followers drive prices away from value (figure 5). This mispricing creates additional profit opportunities for fundamentalists. These profits are realized once prices trend back to value. Because LF-traders have a stronger impact on the dynamics of prices (see figure 5), the profit of fundamentalists is greatest if inducing the LF-trend followers. The conjecture that HF-traders would exploit fundamentalists is not confirmed. In the model, a decrease of the profit of fundamentalists can be caused by the strategy of other traders but not by their speed.

8. Conclusion

In the present study, we used agent-based modelling to explore the effects of High Frequency Trading on financial markets. As its central benefit, agent-based modelling allows uncovering the relationship between the micro behaviour of agents and the macro behaviour produced. The understanding of this relationship can also contribute to understand the effect of HF-traders on market dynamics. The results of the simulation experiments can be used to comment on several conjectures about High Frequency Trading. Table 3 summarizes these conjecture and the answer which suggested by our study.

	Conjecture	Answer suggested by the model
1	HFT increases intraday volatility.	Yes, as HFT market making fosters technical intraday trading. Otherwise, no.
2	HFT leads to a rising Hurst Index.	Rather no.
3	HFT increases the correlation between stocks.	Yes, if HF-traders act as event traders.
4	HFT reduces the attractiveness of fundamental trading.	Rather no.
5	HFT improves market liquidity.	Yes, if HF-traders act as market makers.
6	HFT facilitates the value discovery process.	Yes, if HF-traders act as market makers.
7	Market making will increasingly congregate around HF-traders.	Probably yes.

Table 3: Simulation experiments in relation to conjectures.

In general, we find the effect of HF-traders on market dynamics to be minor than expected. The speed of traders alone does not seem to have a great influence on market dynamics. More important variables are the strategy of traders, their trading volume (catalyzing the effect of the strategy), and the intensity of inventory control. Inventory control is crucial, as with rigorous control, transactions (and thus the impetus of transactions on market dynamics) need to be reversed quickly. As intense inventory control is a typical property of HF-traders, this explains why the effect of a particular strategy is less if executed by HF-traders.

These results underline that HF-traders should not be treated as a homogenous groups. The effect of HF-traders is sensitive to the trading strategy they apply, but even if this strategy works destabilizing, it would work at least as destabilizing if used by LF-traders. Hence, establishing the net effect of HF-traders as a group is only possible if the fraction of each strategy in this group would be known.

Nevertheless, we remind to handle the results of our study with care. Like in all models, the assumption under which the results are obtained must be considered. In this context, we point to the specific design of our model. In the model, passive and aggressive traders were strictly distinguished. This clearly simplifies reality, in which singular traders can accept market orders as well as submit limit orders. It would be interesting to explore if and how results change if particular strategies, such as mean-reversion trading, are applied passively. We refrained from this so far, because a bulk of assumption about the submission of orders would be needed (in particular, about the price at which shares should be offered). Further, there might be alternative designs of trading strategies. Obviously, the trading strategies in the model have been strong simplification of real strategies. Future research might explore if there are aspect of the behaviour of real traders which change the results obtained here.

Another contribution of this study is the model itself. The model was able to mimic the trading action on a micro level within a singular day and produced a very good fit to the real market. As a special benefit the model allows events to occur at arbitrary moments of time. This might be a valuable feature for the exploration of related research questions in which speed is a relevant dimension and small intervals of time are to be considered.

We believe the model to provide several possibilities for adaption and extensions. Firstly, Instead of distinguishing between two groups, speed could be interpreted as continuous with every trader possessing another trading latency. In such a model, more complex insights into the influence of speed of profits and dynamics might be discovered. Secondly, a switching mechanism might be introduced. The model presented so far focused on singular days, and we can assume that traders do not change their behaviour in such a short time. However, if simulating a series of days traders might switch between strategies in dependence of the strategies' profitability. Such an evolutionary model might be used to predict how the population of traders evolves over time and to understand the interdependence of the profitability of strategies. Studies in these directions could extend our understanding on the influence of High Frequency Trading.

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APPENDIX

Proof of Proposition 1

Let price changes be denoted by X. It is well known, that if X is IID

$$SD(\sum_{i=1}^{N} X_i) = \sqrt{N} * SD(X).$$

Further, if X is normal, the expectation of $|X|$, $E|X|$, can be written as

$$E|X| = SD(X)\sqrt{2/\pi}.$$

Combining both equivalences, we get:

$$E\left(\left|\sum_{i=1}^{N} X_i\right|\right) = \sqrt{N} * E(X).$$

q.e.d.

C

Affidavit

Publication of the contributions of the present dissertation

Synopsis:

Unpublished

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Contribution 3:

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Contribution 4:

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Contribution 5:

Witte, B.-C. 2012: „High frequency trading and its influence on market dynamics: insights from agent-based modeling". Unpublished working paper.