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Fundamental traders' 'tragedy of the commons': Information costs and other determinants for the survival of experts and noise traders in financial markets

Björn-Christopher Witte [*,1]

University of Bamberg, Department of Economics, Germany

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ABSTRACT

This study explores the long-standing question about the survival of noise traders in financial markets through the relatively new method of agent-based modeling. We find that, in the normal case, there are two attractors for the ratio of experts versus noise traders. Either experts disappear almost entirely from the market, or they account for a certain fraction, with noise traders still being present. In the dynamic framework, the dynamics switches between these attractors, which leads to the emergence of some typical statistical features of financial markets, such as long memory, leptokurtic returns, and bubbles and crashes. Furthermore, we achieve a general approximation of the attractors and of the switching point in between from relevant determinants.

1. Introduction

Studies on financial markets commonly distinguish between two kinds of traders. Independent of their denotation (some studies call them rational, sophisticated or informed, others speak of arbitrageurs, smart money traders or fundamentalists), the common characteristic of the first group is that they derive their transactions from the analysis of true fundamental information. Though not trading arbitrarily, for the second group, this is not true. For example, so-called technical traders (or "chartists") seek to identify patterns in the evolution of prices and extrapolate them. Yet, because of the myriad of behavioral patterns in this group and the unpredictability of their transactions, the second group has been known as "noise traders" (Black, 1986).

It has been a long time since Milton Friedman (1953) stated that noise traders cannot survive in a market — a proposition which has been replicated in different model setups such as Figlewski (1978), Sandroni (2000) and Blume and Easley (2006). The unifying logic is that noise traders would lose money compared to rational agents as they trade on wrong beliefs (see also Alchian, 1950; Fama, 1965, for early proponents of this view). The opposite view is represented by a profound body of theoretic evidence which indicates that, under more or less restrictive assumptions, the long-run survival of noise traders is possible. Examples include DeLong et al. (1990, 1991), Blume and Easley (1992) and Evstigneev et al. (2002). One of the most popular arguments for this belief has been proposed by DeLong et al. (1991), who construct an overlapping-generations model. If noise traders overestimate returns or underestimate risk, they tend (unconsciously) to accept higher risks than arbitrageurs and thus achieve superior returns on average. Finally, Black (1986) states that noise trading is the very condition for rational arbitrage because if everyone had the same correct beliefs, there would hardly be any trading.

Our study explores the survival of noise versus expert traders in a dynamic agent-based model. Financial market models from this field have proven to be quite successful in improving our understanding of real market dynamics; for surveys, see Hommes (2006), LeBaron (2006) or Westerhoff (2008). The relatively new, simulation-based approach enables us to uncover some dynamic effects in the ratio of trader groups which have been vastly ignored so far.

A key feature of our model is the implementation of information costs. According to Merton (1987), information costs arise from "gathering and processing data". Several studies have found such costs to be influential in investment decisions (e.g. Ahearne et al., 2004; Gregoriou and Ioannidis, 2006; Kang et al., 1999). We can assume that information costs are particularly relevant for expert trading.

* Wissenschaftliches Institut für Hochschulsoftware der Universität Bamberg, An der Weberei 5, D-96047 Bamberg, Germany. Tel.: +49 951/8632499.
E-mail address: bjoern-christopher.witte@uni-bamberg.de.

[1] Dr. Björn-Christopher Witte is a researcher at the Scientific Institute for Software in Academia at Bamberg University (ihb). He graduated from the PhD-program "Markets and Social Systems in Europe" at Bamberg University and lectured at the Department of Economics in the fields of advanced microeconomics and macroeconomics. He has MA degrees in European Economic Studies and Information Systems. For further information, see http://www.unibamberg.de/index.php?id=29501.

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Our model finds information costs to be a crucial determinant for the ratio of experts versus noise traders. Another new insight is that the share of experts, denoted by K, can alternate between two different attractors. The first attractor is $K = 0$. In such intervals, experts avoid the market because, due to the prevalence of noise traders, the tendency of the market towards a fundamental correction is too low to cover information costs. Experts incur profits if K exceeds some level K_1, and the second attractor K_2 becomes active. In K_2, noise traders may still be numerous. The reason is that once K exceeds K_2 the average mispricing becomes too small to make the experts' strategy profitable.

One goal of this study is to derive these conditions of the existence and the value of the two critical points K_1 and K_2. We can do this analytically within a simple static framework (Section 2). In Section 3, the static setup is transformed into a dynamic agent-based model.

The value of the agent-based model is to extend the analytical findings and to review their implications under more realistic conditions. It will be shown that the dynamics of the model switches between K_1 and K_2, and this produces volatility clustering, heavy tails of returns, and speculative bubbles and crashes — three of the most important stylized facts of financial markets. The two-staged approach illustrates the potential of agent-based modeling in combination with static analyses and yields some new insights into the question at stake.

2. Static analysis

In this section, we explore the conditions of the profitability of expert trading against in a simple static model. All symbols that are used here and in the following are summarized in Table 1.

2.1. The model

As described before, experts seek to derive the true value of a financial asset from fundamental data with the intention of gaining profits from mispricing. The strategy rests on the belief that the price, P, of an asset will return to its fundamental value, F, sooner or later. The income of experts corresponds to the fundamental correction, which is equal to $-\Delta|F-P|$. Under the assumption that fundamental trading (Damodaran, 2002; Greenwald, 2004) implies information costs, the profit of one singular expert k, V^k, can be written as follows:

$$V^k = -\Delta|F-P| - \gamma \tag{1}$$

with $\gamma > 0$.

Of course, the fundamental correction $-\Delta|F-P|$, is not given market-exogenously, but results from the activity of traders. Due to their strategies, experts tend to reduce mispricing. Taking this into account, $-\Delta|F-P|$ can be written as:

$$-\Delta|F-P| = K^{1/\beta}(|F-P|), \tag{2}$$

where K denotes the share of experts among all active traders in the market and β is a constant parameter with $\beta > 0$. Eq. (2) stipulates that the fundamental correction $-\Delta|F-P|$ is greater when more experts are active in the market (higher K), since a greater part of the transaction volume relates to fundamental information, and when the mispricing $|F-P|$ is larger, as experts feel incentives to trade more often and in larger volumes. Besides, the actual mispricing sets the upper limit to the possible correction. Only if $|F-P| > 0$ can experts make profits, which amount to a possible maximum of $|F-P|$. The parameter β represents the average trading power of one single expert. A greater β means that the same share of experts reacts more strongly to a given distortion and produces a greater realignment of prices. In the extreme case of $\lim_{\beta \to 0}$, $-\Delta|F-P|$ tends to zero, independent of the values of K and $|F-P|$.On the other hand, a greater K tends to decrease the average mispricing, i.e., $|F-P|$, as experts engage in arbitrage trading. This aspect may be expressed as follows:

$$|F-P| = \Phi(1-K)^{\beta}, \tag{3}$$

where Φ is a positive constant which determines the upper limit of the function. (In the following, Φ will be set to 1). Eq. (3) implies that, aside from the ratio of experts, the average mispricing depends on their trading power β. If β is larger, the same number of experts will keep $|F-P|$ on a lower level. In the extreme case of $\lim_{\beta \to 0}$, $|F-P|$ tends to Φ, independent of the value of K.

By combining Eqs. (1), (2) and (3), the profit of one single expert results as

$$V^k(K) = K^{1/\beta}\left[\Phi(1-K)^{\beta}\right] - \gamma, \tag{4}$$

with $K \in [1/N; 1]$, where N is the total number of traders in the market.

2.2. Model analysis

The static model as represented by Eq. (4) conveys two basic insights. First, the profitability of the expert strategy depends on the total weight of experts in the market, and, second, the relation between both variables is complex and nonlinear. Fig. 1 illustrates the relation graphically. Φ and β are set to 1 and γ to 0.1.[2]

The concave parabola $V^k(K)$ has two zeros, denoted K_1 and K_2, and one maximum denoted K_3. If K is smaller than the "break-even point" K_1, experts lose money, because the influence of experts on prices is not sufficient to create an average price correction which compensates for information costs. As a result, experts will leave the market and K will drop to its minimum. On the other hand, experts incur losses if K is greater than K_2, because the average mispricing is too

Table 1
The symbols used in the article and their specifications. Symbols with (without) time index, t, belong to the dynamic (static) model.

Symbol	Description	Value
Variables		
A_t	Attractiveness of expert strategy in time t	–
$D_{i,t}$	Excess demand of singly trader of type i in t	–
F (F_t)	Logarithmic of fundamental value (in t)	–
G_t	Most recent profit of single expert in t	–
K (K_t)	Share of experts among all traders in the market (in t)	–
P (P_t)	Logarithmic of security price (in t)	–
V^k	Profit of single expert	–
θ_t	Logarithmic of the change of the fundamental value in t.	–
Z	Income of single expert (information cost ignored)	–
Parameters		
a	Intensity of price adaption	0.01
b_1	Reaction speed of experts	100
b_2	Budget constraint of experts	1
γ	Information costs	0.0036
δ	Speed of strategy switching	0.005
η	Memory of agents	0.95
σ_f	SD of fundamental value changes	0.0025
σ_r	SD of demand by singular noise trader	3.2
Derived expressions		
K_1	Lower zero of $V^k(K)$. "Break-even point"	–
K_2	Upper zero of $V^k(K)$. "Carrying capacity" of the market	–
K_3	Maximum of $V^k(K)$	–

[2] DeLong et al. (1990) present a similar graph which describes the share of noise traders when fundamental risks are present. The difference is that in the study by DeLong, the existence of two equilibria is sensitive to the assumption of fundamental risks. Here, the condition is positive information costs.