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THE EFFECT OF DIFFERENT NEEDS, DECISION-MAKING PROCESSES AND NETWORK-STRUCTURES ON INVESTOR BEHAVIOR AND STOCK MARKET DYNAMICS: A SIMULATION APPROACH

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SOM-theme B: Innovation and interaction

Abstract

Striking investor and stock market behaviour have been recurrent items in the worldwide press for the recent past. Crashes and hypes like the Internet bubble are often hard to explain using existing finance frameworks. Therefore, the authors provide a complementing multi-theoretical framework that is built on existing finance research to describe and explain investor's behaviour and stock market dynamics. This framework is built on three main components: needs, decision making theory, and (social) network effects. This framework will be used to build a future simulation model of investor behaviour and to generate stock market dynamics. A brief outline of the design of these simulation experiments will be given.

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1 Introduction

Worldwide financial markets have hit the news in the recent past numerous times due to striking behavior of both (individual) investors active on these markets as well as due to the (sometimes awkward) market developments that resulted from aggregate investor behavior. The two most obvious examples of the last 2 decades are perhaps the stock market crash of 1987 and the Internet bubble of the late nineties of the former century. Both examples will be shortly discussed hereafter.

On Monday the 19th October of 1987, The US stock markets lost to 23% of their value in just one day. Since then, there has been no satisfying explanation why the crash took place on exactly this date, why it occurred so quickly and was played out in one day, why the markets fell so much, why the crash was not merely American, but worldwide and why there were no significant news items or events preceding the crash. Although standard explanations like program trading, overvaluation, events and illiquidity could explain some of the questions mentioned above, none could explain them all. However, the authors expect processes of social interaction and social influence among investors to play an important role in this phenomenon and to be key to a better understanding of this crash.

The Internet bubble is the other example of recent deviant investor and market behavior. In the late nineties of the last century, stock prices of companies related to the Internet or Communication Technology business rose dramatically over very short time spans. Price rises of over 100% in just a few days were no exception. Even the mere announcement of a name change of a company in a name that suggested some connection with the Internet could already cause significant increases in stock prices of these companies (Cooper et al., 2001). Then, after more than a year of rapidly increasing stock prices, the Internet bubble bursted and prices of Internet and Communication Technology related stocks settled at a much lower level. Just as with the preceding example, the authors expect processes of social interaction and social influence to be of importance for a satisfactory explanation of this phenomenon.

Moreover, investor needs; e.g., the need for belonginess or participation, are expected to play an important role.

Our contribution to resolving this puzzle is the development of a behavioral theoretic framework that integrates perspectives from both finance theory, perspectives from decision-making theory as well as social network theory in a sequential way. We argue, that it is necessary to include (psychological, social psychological and sociological) theories on needs, social interaction and network structures in current finance theory to come to a framework that leads to a better understanding and explanation of investor and stock market behavior. The objective is to identify critical micro level factors (e.g., personal needs, social interaction) that drive investor's behavior and to explain macro level phenomena (e.g., bubbles and crashes), which may be the result of aggregate investor behavior. The link between the micro level and the macro level is an explicit objective of our study and an important contribution to the field. To be clear, it is not our objective to replace existing finance theories. The goal is to build on, complement and refine these theories in order to offer a complementing framework. This need is widely acknowledged among finance theorists. (De Bondt and Thaler, 1994; Statman, 1996; Olsen, 1998; Thaler, 2000; Ritter, 2003).

The proposed framework will first be tested on a micro level using questionnaires and in-depth interviews that will be held among Dutch investors. When necessary, the framework will be adapted after the first empirical data are processed. Then we will proceed, using a multi-agent computer simulation method. Using this method it is possible to study the effect of changing assumptions on micro level investor behavior on macro level stock market dynamics. Based on the knowledge gained through first empirical studies, we will formalize the influence of multiple needs, social interaction and network effects on the trading behavior of investors into a multi agent computer simulation model. Here the data obtained from the field study will be used in the parameterization of the agent characteristics. A large number of agents will be used as well as a significant number of different stocks. As institutional/ professional investors cause a major part of the stock turnover, a number of institutional/professional agents should be included as well. Sensitivity analysis will provide information on the sensitivity of the market dynamics for (1) heterogeneity concerning the weight of different needs, thus allowing to test if small proportions of investors weighting social needs do affect the market as a whole, (2) heterogeneity of agents concerning their sensitivity for uncertainty and hence their inclination to use social heuristics, and (3) the shape and size of agents networks. These simulation-generated dynamics will then be compared with empirical data on stock market dynamics. Both the effect of varying the discussed micro level factors on the behavior of investors and the resulting macro level phenomena are topic of investigation; i.e. there will be a coupling of micro level data to macro level data.

The use of computer-simulated markets with individual adaptive agents is a relatively new method in finance (LeBaron, 2000). The simulation models that were developed the last decade range from very simple models like that of Lettau (1997) and Gode and Sunder (1993) to very complex models like the Santa Fe artificial stock market developed by Arthur et al. (1997). Examples of models of intermediate complexity are those by Arifovic (1996), Routledge (1994) and Beltratti and Margarita (1992). Many other models of artificial stock markets exist (for an overview see e.g., LeBaron, 2000). Many of these markets are based on research that distinguishes several kinds of traders (e.g., information traders versus noise traders) and observe the market dynamics after they are put together (e.g., Chiarella, 1992; Day and Huang, 1990). At this moment, there is no simulation model that incorporates all the building blocks of our theoretical framework.

The remainder of the paper is organized as follows. In section two, our theoretical framework is presented. Section three deals with the question how to formalize our framework in a simulation model. Section four gives an outline of the integration of existing simulation models we will use and will briefly describe the first simulation that is planned. The paper ends with a conclusion.

2 An integrated framework on investor behavior

In this section we will introduce an alternative framework of investor behavior. This framework is built on three main components. These are needs, decision-making theory and network effects. In the following these components will be shortly discussed.

Needs

Stocks are traditionally merely associated with the need for financial gains. Although these financial gains may be used to satisfy many different needs (e.g., the need for protection may be satisfied by buying a house, the need for subsistence may be satisfied by buying food), the concept of a single need is by itself quite limited. According to the authors, the act of investing should be studied in a broader perspective of needs.

Much research has been performed on human needs (see e.g., Maslow, 1954; Kamenetzky, 1992 and Max-Neef, 1992). In our framework we choose the needs taxonomy of Max-Neef (1992) as a starting point. The reason for this choice is the level of elaboration of this taxonomy (i.e. it consists of nine different, mutually not-excluding needs, it makes a distinction into needs and satisfiers and it is empirically grounded).

The taxonomy of Max-Neef consists of the following nine needs:

- Subsistence. This need is a very basic one and in fact it aims at staying alive.
- Protection. People need protection. This can range from protection from the weather (by e.g., a house) to protection of their income at old age (by e.g., combining social security, savings and investing).
- Affection. People want to be appreciated and loved by others.
- Understanding. People want to learn new things and develop themselves by studying.

- Participation. People want to be a part of something larger than themselves. They want to share and interact.
- Leisure. People want to spend their free time in a meaningful and fulfilling way and want to have fun.
- Creation. People like making and creating new things. They are curious for inventions.
- Identity. People like integrating themselves and to feel a sense of belonging (or also to distinguish themselves from others). This need has a large social element.
- Freedom. People want to have equal rights and to be free to do what they like to do.

So, the financial benefits harvested from investing may serve to satisfy needs such as subsistence (by buying groceries), protection (by buying a house) and leisure (financing a holiday). However, the act of investing as such may also have non-financial mediated effects on needs. People also may trade for reasons of excitement (leisure) and/or to comply with the behavior of friends (belongingness). Also, some stocks will be bought because one identifies him/herself with the company in question. For example, in the Netherlands many AJAX fans bought shares of this Dutch football club when it issued them in an IPO (Initial Public Offering). It is hard to believe that these investors (only) used a risk/return calculation to come to the decision of investing in "their club". It is far more plausible to assume that these investors (also) tried to satisfy their need for identification with this particular football club by buying these shares. Also for other kind of stocks this reasoning seems appropriate (e.g., for Internet and Communication Technology related stocks). People may even trade stocks to satisfy a need for leisure. For example, private investors sometimes join investor associations to spend their free time in a meaningful way and to have fun. Becker (1991) and Hong et al. (2001) confirm that investors may enjoy talking about stock markets with relevant others (e.g., friends, colleagues, etc).

Decision-making

Decision-making can be either more individual based or more social based. A representative example of a more individual based model[1] of decision-making is the rational model of decision-making as put forth by e.g., Simon (1947). This kind of models focus' the decision makers attention on the different steps in a decision-process that have to be followed to come to a decision. They make sure that no important point is missed or that preliminary conclusions are being drawn. In general, these models consist of three main parts: intelligence, design and choice.

However, when socially oriented needs become important for the investor, more social interaction is likely to take place and more social information will be used in the decision-making process. Social interaction and the use of social information may take the form of heuristics that use social information that guide investors in making their decisions. In general, heuristics are composed from building blocks that guide search, stop search and help to make decisions. The distinctive characteristics of heuristics are that they are fast and frugal. Fast refers to the relative ease of computation of these strategies. Frugal refers to the very limited amount of information that these strategies need (Gigerenzer and Selten, 2001).

In general, the use of social heuristics like imitation and social comparison is driven by two motives. First, in situations of uncertainty these strategies may be both effective (i.e. lead to 'good' decisions) and efficient (i.e. need little time and cognitive processing). Second, these strategies can satisfy one's social needs, like the need to participate. Both situations are likely in an investment setting with private investors, as will be argued in the next sections. It seems likely that investors use different parts of their social network in either of these instances (i.e. using social heuristics to assist decision-making under uncertainty versus using social heuristics to satisfy their social

[1] The reader should note that these models (e.g., Simon, 1947) do not rule out social influence. These influences may for example come to the fore in the design stage, where social interaction may help to generate alternatives. Social influence is however no integrated parts of the model as such, in contrast to for example the EBM model of consumer behaviour by Engel et al. (1993).

needs). We will come back to this in the section on social networks. First the role of uncertainty and social needs will be discussed in more detail.

Uncertainty

Generally, the less information one has with respect to a decision problem, or the more complex and contradictory this information seems, the more uncertain a person becomes.[2] When the level of uncertainty rises, it becomes more likely that a person demonstrates social processing (Festinger, 1954; Bala and Goyal, 1998). This means that this person uses social interaction and social information to help him or her to arrive at a decision. We expect an important role for social comparison and social interaction in the decision making process of private investors. After all, the stock markets are known for their sudden developments and a high degree of information asymmetry between actors (e.g., one investor may be a true finance expert while another is a starting investor). These characteristics of the stock market, coupled with the facts that stocks are intangible and provide no guarantees (although it may be possible to create these by options) and the various types of stocks, create a potential high level of uncertainty for an investor. This situation of uncertainty increases the likelihood of processes of social comparison and social interaction to take place in these kinds of markets. For this reason one can expect an increased use of social interaction and social information (e.g., the use of 'social' heuristics) by investors.

Social needs

When social needs gain importance for investors, the concept of social rationality comes to the fore. Social needs like the need for participation and affection introduce social goals besides the financial goals of investing. In these cases social rationality is the relevant type of rationality besides more traditional (i.e. financial) notions of

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[2] The reviewer brought to our attention the possibility of a situation of abundant information, which may lead to an opaque decision environment and therefore an increased level of uncertainty. Especially in the stock markets this situation seems likely.

rationality. These social goals contain accountability (i.e. making decisions that can be justified and defended (Tetlock, 1983)), transparency (i.e. making decisions that are understandable and predictable by the group with which one associates) and fairness (i.e. making decisions that don't violate the expectations that are in force between people of equal social standing) (Gigerenzer, 2001). Social imitation as a heuristic helps the decision maker in situations of limited time and knowledge to come to decisions. Social norms may play a similar role. Particular in the domain of social rationality these heuristics are important and of value in addition to the cognitive building blocks identified before (i.e. searching rules, stopping rules and decision rules). The concept of social rationality is useful in an investment setting, as it is likely that to many people it is important to make accountable, fair and transparent investment decisions.

In current financial theories, however, no framework is developed in which processes of social comparison and social interaction are seen as regular parts of investors' decision making, although the occurrence and benefits from this kind of behavior in an investment setting are slowly being acknowledged (see e.g., Shiller and Pound, 1989; Orléan, 1989; Fung and Hsieh, 1999; Kelly and O'Grada, 2000; Hong et al., 2001 and Hirschleifer and Teoh, 2003).
However, before any product or decision can become socially relevant, it should be visible (i.e. other people should be sensorial (e.g., see, hear, etc.) informed about the decisions you have made). Other people (e.g., in your social network) should be able to see what decision(s) you have made (e.g., buying shares of Unilever, Royal Dutch, etc.) Although in general one could argue that stocks are not very visible in a strict visual sense (e.g., compared to for example a car) discussing about stocks at parties and joining investor associations may increase this visibility. The information diffusion characteristics of social networks may further support these processes by transporting information about share ownership to a mass of other investors.

Social networks

Before people can trade using information gathered from people they know, like friends and colleagues, they should interact to become aware of this information and to get this information. This information is being spread through networks, connecting friends with friends from friends and so forth (Watts and Strogatz, 1998; Watts, 2001, Janssen and Jager, 2003). Recent research demonstrated that many large networks display a scale-free power-law distribution for node connectivity (Barabasi & Albert, 1999). In terms of market dynamics this may imply that a small proportion of investors having a lot of contacts (so-called 'hubs') may have an exceptional influence on the investing behavior of others. We expect these hubs to differ in certain characteristics (e.g., uncertainty, status) compared to non-hubs. In the context of markets, much attention has been focused at networks between "buyers" and "sellers" (e.g., Ford, 1997). This approach contributed to the understanding of certain empirical phenomena, which could not be explained by assuming markets to consist of unstructured aggregations of individuals (e.g., Wellman & Berkowitz, 1997: 221). However, whereas many studies focused on the role of social networks in buyer-seller relationships, hardly any tried to reveal how consumer networks, such as assumed between (private) investors, affect market dynamics. In the stock markets, finance experts or "gurus" may act as connectors and hubs. Having a lot of contacts and expertise at the same time they could have an important influence on the behavior of other investors and an exceptional influence on stock-market dynamics. Lohse (1998) and Hirschleifer and Teoh (2003) illustrate the possible influence of hubs in the stock markets by discussing the endorsement effect of so-called 'anchors' in the stock market. In the preceding sections we discussed the two main reasons for using social interaction and social information in investment decision-making. The main difference between the two is that one is more informative oriented, while the other is more normative oriented. The informative part will be discussed first.

First, social networks can support an investor's decision-making when he or she is uncertain about what decision to make. This is the informative function of the social network. Information about the actions and beliefs of other (comparable) investors in one's social network can assist the investor in his or her decision-making. In this case, it seems likely that an investor socially compares with or imitates another investor with a good reputation (who preferable has a comparable risk preference, income and investment time horizon). Following the behaviour of a finance expert seems more likely to lead to good investments than following the advice of an arbitrary neighbor or friend (assuming these people are no finance experts).

Second, the use of social heuristics can lead to the satisfaction of social needs of an investor. This is the normative influence of a social network. For example, to satisfy the need to belong to a group, one may purchase stocks that are popular among friends, colleagues or whatever reference group one has. It is likely that these friends and colleagues constitute a different part of someone's social network than the before mentioned finance experts.

So, we expect that different parts of investors' social networks are used to achieve different objectives (e.g., supporting decision-making under uncertainty or satisfying social needs) and that different information is transmitted between the persons in these different parts of the social network.

3 Formalizing the framework

The assumptions of our theoretical framework will be used in building a multi-agent simulation model. This model should be able to incorporate the effect of varying levels of social versus individual needs and of varying levels of uncertainty on the behavior of investors and on the resulting stock market dynamics (e.g., price fluctuations, herding behavior, social comparison behavior). The model should have the possibility to vary the numbers of different types of investors (e.g., institutional investors as well as individual investors) and to observe the effect on investors' decision-making and stock market (price) dynamics. It should be possible to study the effect of varying social network structures (e.g., regular grid, random and scale free networks) on the behavior of investors as well as on the stock market dynamics. Furthermore, the model should include the possibility to generate longitudinal data.

The above-mentioned requirements are quite demanding. However, the authors already have a multi-agent simulation model at their disposal that is based on the *consumat* approach. The consumat approach (Jager, Janssen & Vlek, 1999; Jager, 2000) provides a tool that allows one to formalize needs and different decision processes in artificial agents. Therefore, it is capable of formalizing social needs and social decision processes in a multi-agent computer simulation. The consumat approach is based on a more psychological based meta-theory of human decision-making than the frequently used 'rational actor' approach. In the consumat approach, basic human needs and uncertainty are regarded to be the driving factors behind human decision-making processes. The approach even allows for modeling different network-structures, and has been used to study market dynamics (Janssen & Jager, 2001, 2003).

More formally, there is a population of N agents where each period the agents make a choice which of M products to consume. The agents are connected with, on average, k other agents. These connected agents are called friends. Products are assumed to differ from each other in a dimension d, which is defined for a range from 0 to 1. The utility of using a product consists of two parts; both an individual part and a social effect part. The individual part expresses the difference between personal preferences of a consumer for each product and the product dimension. The preference for product i, p_i, is expressed by a value between 0 and 1. The utility for the product, based on personal preferences alone, is equal to one minus the absolute difference between personal preference p_i and product dimension d_i. The social effect holds that if more friends consume the same product, the utility of the product increases. The variable x_j denotes the fraction of i 's friends who also consume product *j*. The total expected utility of consuming product j is equal to:

- $E\,[U_{ij}] = (1 - \beta_i)\,(1 - |\,d_j - p_i|\,) + \beta_i\ x_j$

The components of the utility function, the individual part and the social part, are weighted with 1-β_i and β_i. A low β_i holds that personal needs are weighted more, whereas a high β_i holds that the social needs are weighted more. Prices are not explicitly included in the model. However, the dimension d_j on which the agents make decisions may include price related information. So, at two levels there is an introduction of heterogeneity in the utility function of the agents. First, there exist individual variations considering personal preferences regarding the product characteristics, the value of p_i. Second, it resides in different weights of the personal need against the social need, the value of β_i. This β value can also be seen as a decision-makers social susceptibility.

Although the explicit formalization of the consumat approach is not directly translatable to an investment setting, the *approach* as such has many strong points (e.g., the possibility to vary the extent of social susceptibility of decision makers, the option of using different networks of decision-makers and most importantly the strong base of the approach in theories on human decision-making). The approach fits well with our framework, which is also based on theories of human decision-making. For our current aims however, the approach still has two limitations. First, the approach does not include prices of the products. Second, the approach is able to generate ‘hypes’ and ‘crashes’ of products, but is unable to generate more complex volatility, as it is often seen in the stock markets. We believe that introducing a price mechanism will solve both problems. We intend to achieve this by incorporating critical parts of the consumat approach into an established simulation model originating from finance.

A number of agent-based simulation models exist in finance, reaching from very simple to highly complex models (see e.g., Bray, 1982; Grossmann and Stiglitz, 1980; Kareken and Wallace, 1981; Day and Huang, 1990; Chiarella, 1992; Gode and Sunder, 1993; Routledge, 1994; Arifovic, 1996; Arthur et al., 1997; Lettau, 1997; LeBaron, 2000). The authors are basically interested in the effects of including social needs, social interaction and network effects in finance models on the trading behavior of investors, price dynamics as well as in any possible interaction effects between the foregoing (e.g., the effect of severe price volatility on investors’ trading behavior). Therefore, and because we already have a multi-agent simulation model at our disposal, the finance-based simulation model that is added to our approach should be an accepted, simple, although realistic, model. For these reasons, we decided to use the model by Day and Huang (1990) that they present in their often cited (44 times[3]) paper “Bulls, Bears and Market Sheep” as a starting point in our analyses.

[3] See e.g., http://isi4.isiknowledge.com/portal.cgi?DestApp=WOS&Func=Frame

4 Integrating multi-agent simulation models

In this section we will first discuss the model by Day and Huang (1990) that we will use in our future simulations and then discuss the design of these future simulations.

4.1 The model of Day and Huang

Day and Huang (1990: 299-300) start their argument by posing the following question:

"…Is it possible that observable features of stock market prices, such as their unpredictable, fluctuating nature and their tendency to generate alternating periods of generally rising or generally falling prices, so-called "bull" and "bear" markets that seem suddenly to switch from one to the other at irregular intervals, are derivable from the way market participants behave?"

According to Day and Huang (1990), this first question is in contrast to conventional arguments, which state that opportunistic trading by rational investors will arbitrage away any possible gain from predictable stock market patterns, so that any movement in stock prices is caused by more-or-less random news. However, it matches very well our framework, which expects that psychologically and socially based market behavior of (networks of) investors cause stock market dynamics. More generally, other authors admit that psychological forces are in play at instances of striking stock market dynamics (see e.g., Shiller, 1987 and Smith et al., 1988). Day and Huang build a model of excess demand and price adjustment that is "just sufficient" to answer the above-mentioned question (Day and Huang, 1990: 300).

The model contains three types of market participants: α-investors, β-investors and the market maker. We will briefly describe here the market behavior of these three types of market participants, for a detailed discussion we refer to Day and Huang (1990).

α-investors

The α-investor uses a strategy based on an independent, sophisticated estimate of the long run investment value *u* in relation to the current market price *p* and on an estimate of the probability of capital gains and capital losses. The investment value *u* is the α-investors' best estimate of the price if anticipated long run economic conditions actually came to dominate the future. It is based on e.g., statistical analyses of trends in aggregate economic variables and individual company performances. These quantitative estimates are then adjusted with the help of 'soft' judgments based on e.g., journals, papers, magazines and direct company observations. The properties of α-investors demand function are so that:

- when *p* is below *u*, investors are net buyers of shares,
- when *p* is above *u* they are net sellers of shares,
- and when *p* is equal to *u* investors hold their current stocks, i.e. there is no excess demand.

The beliefs of the α-investor can be compared to the beliefs of the investor in the model of investor sentiment by Barberis, Shleifer et al. (1998) in the situation when the investor beliefs the world to be governed by regime 1. In regime 1, earnings are determined by model 1, which holds that earnings are mean reverting. In the model of Day and Huang (1990), the α-investor sells if the price reaches a level above the long run investment value and buys when the price reaches a level below the long run investment value. Apparently, the α-investor has the belief that prices revert back to the long run investment value (i.e. the "mean" in Barberis, Schleifer et al. (1998)).

More formally, the excess demand function for the α-investor is:

- $\alpha(p)$: = a(u-p) f (p) for p ε [m, M]

- $\alpha(p)$: = 0 for $p<m$, $p>M$

This function is bounded on an estimated topping price M and an estimated bottoming price m. The assumptions of Day and Huang with regard to the effect of M and m are:

- If $p < m$, investors will have bought in already, then no excess demand

- If $p > M$, investors will have sold out already, then no excess demand

The positive parameter 'a' is a measure of the strength of investor demand. It reflects the fact expressed by Black (1986) that the farther the price of a stock is from its long run investment value, the more aggressive the information traders become.

f (p) is a weighting function that represents the chance of lost opportunity caused by either failing to buy when the market is low or failing to sell when the market is high. When p is close to m, the chance of missing a capital gain by failing to buy is great, when p is close to M, the chance of losing a capital gain and experiencing a capital loss by failing to sell is great as well. When p is close to u, the perceived chance of capital gain or capital loss is small or zero. So, f (.) is bimodal with modes near or at m and M. Formally:

- f (.) is non-negative, differentiable and bounded on [m, M].

- $f'(p) < 0$ for $m < p < u$

- $f'(u) = 0$

- $f'(p) > 0$ for $u < p < M$

β-investors

The β-investors, similar to Blacks' (1986) 'noise traders' do not pursue the same sophisticated techniques as the α-investors, as this trading is expensive: it takes a lot of time, costly information and a substantial investment in intellectual and computational capital. Most market participants therefore cannot afford to pursue this kind of behavior and accordingly they don't (Day and Huang, 1990). The β-investors make their decisions using a simple comparison between the current price *p* and the current fundamental value, *v*. In the model of Day and Huang (1990), the value of *v* is given. The authors do not mention the way *v* is calculated. These β -investors believe that the market will go up when the current price is above the fundamental value and that the market will go down when the current price is below the fundamental value. This is a sharp contrast to the α-investors. The β-investors have a demand function so that:

- when *p* is above *v* they are net buyers,
- when *p* is below *v* they are net sellers,
- and when *p* is *v* they hold.

The beliefs of the β-investor can be compared to the beliefs of the investor in the model of investor sentiment by Barberis, Shleifer et al. (1998) in the situation when the investor beliefs the world to be governed by regime 2. In regime 2, earnings are determined by model 2, in which earnings are trending. In Day and Huang (1990), the β-investor is buying when the price is above the current fundamental value and sells when the price is below current fundamental value (i.e. the investor thinks prices are trending).

More formally, the excess demand function for β-investors (after some simplifications) is:

- $\beta(p) := b(p - v)$

The coefficient b reflects the relative importance of β-investors and the strength of their response to price signals.

The market maker

The third participant in the market is the *market maker*. This party is a mediator between transactions on the market and sets a price according to the total excess demand or total excess supply there is in the market and at this price supplies excess demand from his or her inventory of stocks or increases his or her inventory of stocks in case there is an excess supply.

More formally, the total excess demand E is:

- $E (p): = \alpha (p) + \beta (p)$

If V_t is the market makers inventory of stocks at the time he or she announces the price, then the change in inventory is:

- $V_{t+1} - V_t = E (p_t)$

The price change $p_{t+1} - p_t$ is determined by a continuous, monotonically increasing function $c\gamma [E (p)]$ where $\gamma (0) = 0$, where c is an adjustment coefficient and
$p_{t+1} = \theta (p_t): = p_t + c\gamma [E (p_t)]$.

For simplicity, Day and Huang assume $\gamma [E (p)] \equiv E (p)$, so that:

- $P_{t+1} = \theta (p_t): = p_t + cE (p_t)$

Initially, the value of the parameter c is set to 1 in Day and Huang (1990)

The model of Day and Huang (1990) incorporates a few striking features of actual stock market structures, but is designed in a way to reflect “well established stylized facts described by such scholars as Keynes, Williams, Black or DeLong et al., and by expert market players like Ney” (Day and Huang, 1990: 323). Not only are the assumptions plausible, the model also generates data that reflect the real world (i.e. erratic fluctuations, switching bull and bear markets and the volume is concentrated at the tops and bottoms of these regimes) (Day and Huang, 1990). However, the model does not include a needs and social network perspective as we put forth in our framework. Including these perspectives in the model by Day and Huang (1990) will make it more realistic and we expect to generate more plausible price dynamics with an adapted version of the model.

4.2 Future simulations

The first thing that is planned is to try and replicate the results of the Day and Huang (1990) study in our own simulation environment. For this, the model of Day and Huang will be incorporated in our existing simulation model. In the benchmark situation, we will exclude any effect of different needs, social interaction and social networks to run the Day and Huang (1990) model in its pure form. Then, we will include needs in the model. This will be formalized by adapting the formula for investment value of the β-investors.

As we assume that satisfying a social need increases the utility of an investment to an investor, we will add a term to the formula for investment value that causes the investment value to increase as more investors in the social network of the investor in question buy the same stock. Off course, investors differ to the extent of perceiving this need as an important need. Therefore, we introduce a new parameter S (social ‘susceptibility’). This parameter, that is comparable to β in the consumat approach, is initially normally distributed between 0 and 1, resulting in a heterogeneous population of agents. An S value of 0 indicates that an investor only cares about the investment value as before in an individual way (i.e. he or she is comparable to an α-investor), without any social needs. An S value of 1 indicates that an agent only cares about social needs. This is somewhat comparable to the behavior of a β-investor, to the extent that he or she only takes into account what the market (i.e. the investors around him or her) are doing.

The formula for total excess demand will initially be changed according to the assumption that the α-investors have a S_α value of 0 and the β-investors have a S_β value of 1. The average S value S, which will be used in the formula is then a representation of the proportion of α- and β-investors that are in the market. To account for the social normative influence, the part of the formula for total excess demand that represents the demand of a β-investor will now not be dependent on the difference between price and average current fundamental value, but on the difference between the price and the average current fundamental value of investors' neighbours in the social network (v_n). We assume that the neighbours only have a current fundamental value to communicate if and only if they own stocks themselves. Then, we can observe that if S = 1 (only social needs), but not a single neighbor of an investor owns a stock, this investor won't buy stocks either. This social influence effect will increase in strength as more investors in someone's social network buy the same stock. Therefore, we introduce the parameter x_j, the proportion of someone's social network that buys the same stock. The total excess demand function will then be:

- $E(p) = (1-S)(u-p) f(p) + S(1 + x_j)(p - v_n)$

The first part of this formula, $(1-S)(u-p) f(p)$, represents the excess demand for α-like investors. The second part of the formula, $S(1 + x_j)(p - v_n)$, represents the excess demand for the β-like investors. The market maker will generate the price in the same way as in the standard Day and Huang (1990) model. By including this effect in the model we expect to generate more realistic market dynamics than with the standard model.

Besides the normative influence of investors in a social network, there's an informative component of social network effects. Social networks facilitate the exchange of information between investors. This can be information on the long run investment value, the current fundamental value or the behaviour of other investors. This information can spread in different ways through the network (e.g., reaching a random node or a hub) and this is expected to have a different effect on the decision-making of investors. Besides the information on the behaviour of the other investors, there are two pieces of information that are distributed trough the network, i.e. the long run investment value u and the current fundamental value among an investor's neighbours (which average is v_n). We start the simulations with 'giving' all investors a different long run investment value u that is normally distributed (e.g., around some historical mean) between m and M. Also, a current price p will be set in a random fashion between m and M. Lastly, all investors will get a different current fundamental value v that will follow a normal distribution (e.g., around some historical mean) between m and M. So, a heterogeneous group of investors will result, with different values for u and v. After this initialization, we will spread changed values of u and v into the network. This represents the changing of opinions among investors about the true value of u and v. The spreading process will be carried out in different fashions; i.e. giving u or v to a random node, giving u or v to the least connected nodes, giving u or v to the main hub (the hub with the largest number of outgoing links), giving u or v to another hub, and the like. We expect different dynamics for the different ways of spreading this information in the network.

After these runs, we plan to test for the influence of different structures of social networks. Different types of social networks (e.g., regular ring network, scale free network, random network) are expected to differ with regard to their influence on the trading behaviour of the various market participants, as the various network structures display different information diffusion characteristics (Cowan and Jonard, 2004). The scale free network for example, with its long-distance links and well-connected hubs, has proven to be very important for the spreading of behaviour (see e.g., Barabasi, 2002). Varying the degree of connectivity as well as the number of hubs is expected to have a strong effect on the behaviour of the agents and therefore on the stock price dynamics.

5 Conclusion

In this paper, a framework on (private) investor behavior was presented. Complementing the views on finance till now, in which scholars assumed that mainly risk and return could explain investor behavior, it is argued that also needs, social interaction and (social) network effects are key to understanding micro level investor behavior and macro level stock market dynamics. In future research, empirical (e.g., questionnaires and experiments) and simulation techniques will be combined. In this research, the actual needs investors try to satisfy by investing will be brought to light, as well as the extent to which social interaction, the use of social information and social networks plays a role in their investment decisions. Using simulation techniques, the effect of this micro level investor behavior on stock market dynamics will be studied.

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