Combining empirical data with multi agent social simulation: investigating micro - macro links in behavioral finance

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1. Introduction

It is Monday morning, and John Smith is on his way to work. During the one-hour drive to get to his office, he realizes what he promised his wife this weekend. This week, John would decide upon steps how to invest the large sum of money they unexpectedly inherited from a far-away relative. John and his wife were quite certain, that with the current low interest rates, they had to invest the money on the stock market. Otherwise, every year, inflation would be allowed to eat into the real value of the inheritance. However, they were uncertain regarding to what securities they should invest in. As John has (1) little investment related knowledge, is (2) not that experienced with investing and (3) realizes how much his family's future financial well-being may depend upon making the correct investment decisions, he perceives the risk of investing to be high. Fortunately, John has a colleague at work with whom he is befriended and who has lots of investment experience and, perhaps even more important, has proven to be a successful investor. John decides that he will ask his colleague for investment advice and immediately feels reassured.

Let us assume, that there are in fact investors like John, who perceive a high level of risk when making investment decisions.[i] When these investors make their investment decisions it is more likely that - due to their low level of confidence - they trust to a great extent on social information. [ii] This social information is gathered by these investors by asking other investors, to which they are related through their social network, for (1) investment advice or (2) for information in the form of their expectations on (specific) stock prices. When the proportion of low confidence investors in a stock market increases, the chances are greater that there will be a growing discrepancy between the fundamental value of a stock and the value that investors perceive a stock has. After all, if an increasing number of investors rely on their social network to form their expectations about the value of a stock and base their investment decisions on this, it becomes more likely that herding behavior, the corresponding stock price inflation, and increased stock market volatility occurs. So, investment strategies that at a micro level are intended to reduce the *perceived* risk of individual investors, might *actually* - by laying a fertile ground for macro level effects like e.g., hypes and crashes - make investing more risky.

We aim for a better understanding of puzzles on financial markets like the Internet hype, or more recently, the explosive increase of Google's or Tom Tom's [iii] stock price. To achieve this better understanding, we follow a research approach consisting of four critical steps that together constitute a complete empirical cycle.

The first step in trying to understand this kind of empirical puzzles is to use multi-disciplinary theory to formulate specific hypotheses with regard to the behavior of the individuals or institutions that are central to the study. In our case, this resulted in performing an empirical study on investor behavior in The Netherlands. In this study, of which part of the results are reported in Hoffmann, Von Eije and Jager (2006), a questionnaire was used to investigate e.g., to what extent individual investors have needs that deviate from a risk/returns perspective. Moreover, differences in the amount of investment-related knowledge and experience of these investors were studied. Furthermore, the effect of these differences - which result in different levels of confidence - on the conformity behavior of these investors was examined. It was found, that individual investors do have other, more social needs apart from their financially oriented needs. In fact, investors that gave a higher importance to social needs and/or who had lower levels of investment-related knowledge and experience, displayed more normative and informational conformity behavior. Normative conformity behavior is the expression of an individual's desire to comply with the positive expectations of others. Informational conformity behavior is the expression of an individual's tendency to accept information from others as evidence about the reality (Deutsch & Gerard, 1955).

The second step, after having increased one's knowledge about micro level behavior, is to discover the effect of (social) interactions amongst micro level subjects on macro level institutions. In our case, this means investigating the effect of interactions amongst micro level individual investors on macro level overall stock markets. This step from the micro to the macro level is an essential one and Multi Agent Social Simulation is an excellent tool to make this step. Although one could argue that conventional mathematical theorizing is also capable of investigating the macro level effects of micro level rules, agent-based computational modeling is a better match for our research problem. Agent-based computational models make it (1) easy to limit agent rationality, (2) facilitate heterogeneity in the agent population, (3) generate an entire dynamical history of the process under study, and (4) make it easy to have agents interact in social networks (Axtell, 2000). By formalizing individual investor agents that are equipped with empirically validated behavioral rules, one can create an artificial stock market that resembles real stock markets in many ways and generates macro level data, like stock market prices and returns over time.

The third step then is to estimate the empirical plausibility of the macro level stock market price and return data. To what extent does the simulation model using empirically estimated agent rules generates empirically realistic and meaningful macro level data? To answer this question, one has to compare the macro level data that are generated by the simulation model with empirically found macro level data. In our situation, this translates to comparing e.g., the volatility and/or the occurrence of possible stylized financial market facts (Cont, 2001) in the price and returns time series of the simulation experiments with those of a representative empirical stock market.

Successful execution of these first three steps would result in a level 3 multi-agent simulation model as described by Axtell & Epstein (1994). In general, the application of multi agent models for financial markets is driven by a number of empirical puzzles or stylized facts (e.g., time series predictability, volatility persistence, and fat tails in the asset returns distribution) that are difficult to explain using traditional representative agent structures (LeBaron, Arthur, & Palmer, 1999). In this sense, our work should be positioned in the literature on building artificial financial markets using computer experiments (see e.g., LeBaron (2000,2005) for an overview). Also, the more specific field of finance that is concerned with the more behavioral aspects of investors' decision-making and financial markets, behavioral finance, is using this method (see e.g., Takahashi & Terano (2003)). However, we deviate from the existing literature by combining in a single study the use of empirically validated micro level agent rules with an empirical evaluation of the macro level outcomes (i.e. the time series of returns of the simulation model). We do not know of the existence of any multi agent social simulation model in behavioral finance that aims and achieves quantitative agreement on both a micro and a macro level with the empirical reality and that therefore constitutes a level 3 model (Axtell & Epstein, 1994).

The fourth step, and one that should not be overlooked, is to take action upon the results of step three. Safe from the exceptional case of a complete match of the simulation generated data with the empirical data, one should investigate the possible causes of the lack of fit between the two and decide upon steps to improve this fit. Possible steps most generally consist of a reconsideration of the first three steps. That is, more detailed empirical research on a micro level might be performed, existing agent rules might be modified or new ones created, or a more appropriate empirical benchmark to compare the simulation generated macro level data with might be searched for. The latter can be necessary when the empirical time horizon (daily, weekly, or monthly) and the time horizon implied by the simulation model are incompatible. See e.g., Lux (1998) for practical examples of dealing with this type of problems.

The process outlined above, i.e. the four critical steps of our research approach, are iterative. In scientific practice, one has to go through the empirical cycle several times. Currently, we have completed the empirical cycle for the first time. That makes our work both interesting for researchers in the field as well as of an explorative nature.

In the next three sections of this paper, will first briefly introduce the multi agent simulation model of investor behavior that we have developed, called SimStockExchange© [iv] Second, we will give the first time user three examples of interesting parameter settings of the model. Third, we will conclude with a perspective on the type of research questions one can address using our simulation model and outline the future of our research program.

2. The simulation model

In Figures 1, 2, and 3, the general settings panel, the stock settings panel and the Repast control panel of SimStockExchange (SSE), respectively, are displayed.

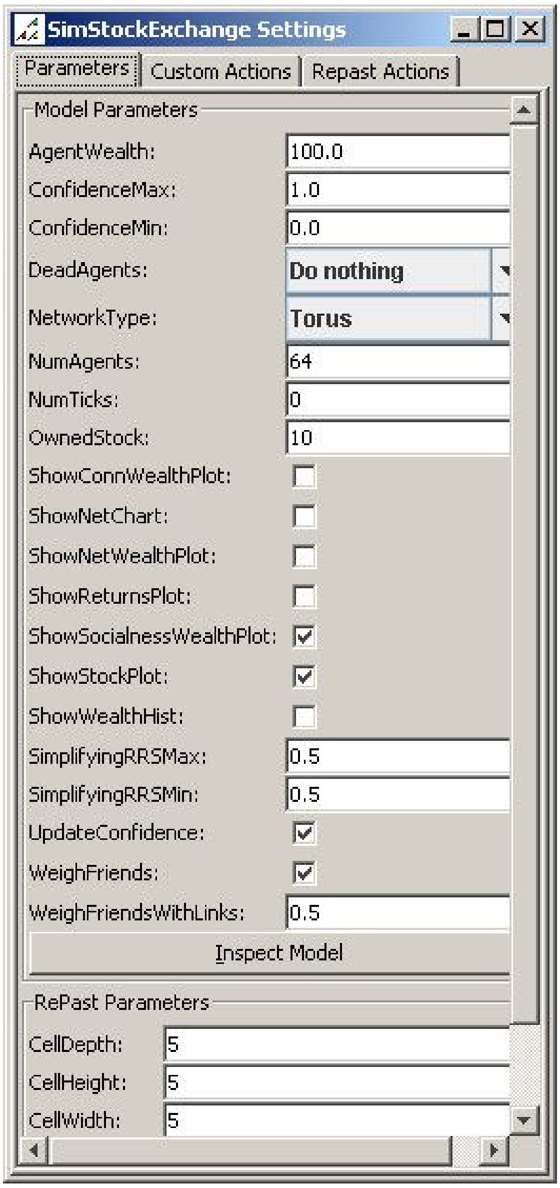

Figure 1: General settings panel of SimStockExchange.

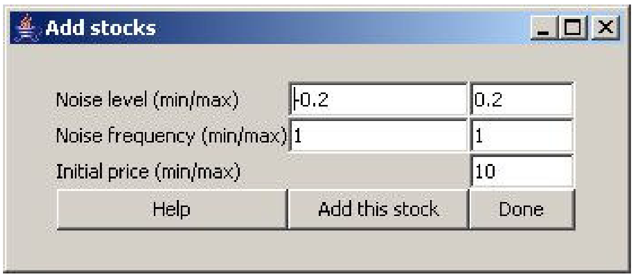

Figure 2: Settings panel of SimStockExchange to add different stocks.

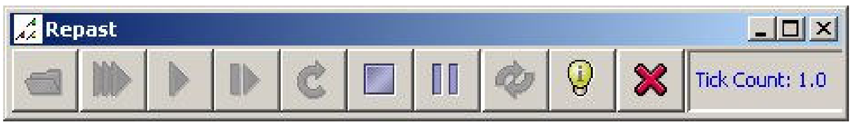

Figure 3: Control panel of Repast.

On the SSE, investors have the possibility of investing all or part of their budget in a number of different stocks or keeping all or part of their budget in cash. Each time period, investors observe a current market price which is the same for every investor and they have an individual expectation of the next period's price. The expectation of the next period's price is based on news that enters the market. This news is randomly distributed within a certain bandwidth around the current price.

At the beginning of each simulation run, every agent is given a budget of both cash and of a number of stocks that it has in portfolio. In case agents lose their complete budget, they are declared bankrupt by the simulation model and do no longer participate in the market interactions of the model. The possibility exists to either replace these bankrupt agents with similar new agents or not to replace them.

In every time step, each agent has to decide how much of his budget to invest in the risky stock and how much to keep in a risk-free asset. To determine which part of its budget an agent will invest in the risky asset, an agent weighs the deviation of the current price from the expected price for the next period by the current price. The resulting percentage is fed through a function that represents the risk averseness of the agents; the more the current price deviates from the expected price for the next period, the more the investor will invest or divest.

Moreover, the agents have different levels of confidence C in the correctness of their own signal that they get about the expected next period's stock price. This property of the simulation model represents the empirically found fact that in real markets investors differ in the amount of investment related knowledge and experience that they have and therefore perceive different levels of risk. In order to reduce this risk, these investors can perform one or more risk reducing strategies (RRS). Examples of RRS (see e.g., Mitchell & McGoldrick (1996)) are the before mentioned normative and informational conformity behaviour. In our empirical study (2006), we have found that when investors have less investment related knowledge and experience, and therefore are regarded to have less confidence, they display both more normative and more informational conformity behaviour. Therefore, when agents are uncertain, they will use information from their social network in their decision-making. C is bounded between 0 (no confidence) and 1 (complete confidence). C can be set as one value for all agents (homogeneous markets) or as a uniform or normal distribution between a minimum and a maximum level (heterogeneous markets).

The extent to which an agent is more inclined to use a normative or an informational strategy is weighed by the parameter R (risk reducing strategy). R is bounded between 0 (only using an informational strategy) and 1 (only using a normative strategy). When using an informational strategy, the agent asks its neighbours in the social network what price they expect for the next period. There are three options how to subsequently weigh these different expectations: (1) use an unweighted average, (2) weigh the different expectations according to the number of links the respective agents have, simulating the proposition that information from heavily connected hubs is of more value and importance than information from any neighbour in general (Barabasi, 2002; Ford, 1997; Newman, 1999; Wellman & Berkowitz, 1997) or (3) weigh the different expectations according to the returns the respective agents have. The last option is an example of a "do-what-the-successful-individuals-do" strategy (Laland, 2002).

When an agent uses a normative strategy, it observes the investment behaviour of its neighbours and looks whether there are more selling or more buying agents. It will decide whether to buy or to sell depending on what action is dominant among its neighbours. After it has identified what action is dominant, it will conform to this action. This is an example of a "do-what-the-majority-do" strategy (Laland, 2002). However, it is not enough to know whether to buy or to sell, the agent also has to know how many shares to buy or to sell. In order to decide how many shares to buy or to sell, the agent will take the average value of the expectations of the next period's price of the group of investors (buyers or sellers) whose decision it decided to copy.

In the preceding section, no distinction was made between different social network structures. In reality, however, there are a number of different social network structures, which differ in their information diffusion characteristics (Cowan & Jonard, 2004). Our simulation model allows for formalizing and experimenting with different types of social network structures.

According to the rules as described above, it is now clear how much of its budget each agent is willing to invest (by buying shares) or divest (by selling shares). However, at what price the shares will be traded is not yet discussed. To determine the price, an order book system is used. Based on the expectations of the next period's stock price, buying and selling agents will forward their maximum buy and minimum sell prices, respectively, to the market. In the situation that it is not possible to cross a complete order, an order can be partly executed and the part of the order that can not be executed stays in the order book. The processing of all orders follows the FIFO principle (First In, First Out).

The market price that is realized in each time step is calculated as the average of the bid and ask prices that are present in the order book, weighted by the number of asked and offered shares. In this way, we account for the price pressure that is put on the market by the bid and ask orders. Even when not all the orders are executed, they still influence the market sentiment and therefore the price level in one period. After that, the presence of the unexecuted orders are known to all market participants and therefore have no influence on the market price anymore.

We are able to incorporate an unlimited number of different stocks in the simulation model; each with different starting prices, different news bandwidths, and different frequencies of news arrival. In reality, however, including more than e.g., 2 or 3 different stocks in the simulation model hampers the analytical tractability. Even when there is more than one stock in the simulation, the investors in our model can only make one sell and/or one buy decision at a time.

Many simulation models are confronted with the critique, that there is no feedback mechanism from macro-level model dynamics to micro level agent strategies or rules. The market dynamics are generated by the actions of the investors, but the cognition of the investors is never affected by the evolution of the market. In order to make the model both more interesting and more realistic, we have included a feedback mechanism (Arthur, 1995). In our model, we introduce a feedback mechanism that relates the successfulness of the agents with its choice of different strategies or rules. Agents with higher returns, who are more successful, get higher levels of confidence in the correctness of their own signal and in the correctness of their own strategies or rules. Therefore, an agent's level of confidence C increases with increasing returns of the agent.

3. Three interesting parameter settings for first-time users

The extensiveness of the simulation model that we present in this paper implies a plethora of possible experiments. In this section, we will discuss three starting points that we deem to be useful for the first-time user. Naturally, we encourage every researcher to start its own voyage of exploration and establish its own opinion about the richness of our model. However, in order to get an initial feeling for the model we advise the first-time user to start with the three experimental settings we will now touch upon.
In all three experiments, we will keep the following parameter settings constant:

- The agents have an initial wealth of 100.
- Agents that go bankrupt are not replaced by new agents.
- We use a simple Torus network.
- We set the magnitude of the news (noise) to 0.2.
- There will be 1000 agents active on the market.
- There will be only 1 stock traded on the market.
- We let the simulation run for 1000 time steps.
- Every agent initially has 10 stocks in its portfolio.
- The proportion of informational versus normative conformity behaviour is set to 1.0 (SimplifyingRRS=1.0).
- The initial stock price is 10.0.
- We update the confidence of the investors according to their returns.
- We select weigh friends, and set it to 0.5.

In the first series of experiments, we will systematically vary the level of confidence of the agent investors and investigate the effects of this on the stock market volatility. Every agent will have the same level of confidence, that is, we will assume a homogeneous stock market. This is formalized by setting the "ConfidenceMax" and "ConfidenceMin" at the same values. One starts with a level of 1,0 (complete confidence) and gradually lowers this in steps of 0,10 to a level of 0,0 (no confidence). After opening the log files [v] and reading them into a statistical program, one plots the data in a graph. Now we can observe the relationship between the level of confidence and the stock market volatility to have an inverted U-shape. In markets that are dominated by investors with very low levels of confidence and markets that are dominated by investors with very high levels of confidence, the volatility is relatively low. In the first type of market, investors rely almost completely on their social network to make their decisions and almost ignore their own news signal. As the network size is limited, after a short while, all investors share the same information and want to make similar investment decisions. This leads to an imbalance in the order book and no or only a few orders will be executed. Without executed orders, the market price remains stable and the volatility is either very low or absent. In the second type of market, investors rely almost completely on the news that they receive and there is hardly any social interaction or herding behavior that comes along with social interaction. Therefore, hypes and crashes are less likely and the volatility of the stock market is merely a mirror of the volatility of the news that reaches the stock market. At intermediate levels of confidence however, there are both investors for whom social interaction and conformity behavior plays an important role as well as investors that are more strongly influenced by their individual news signal and no group of investors clearly dominates. This diversity in the market gives rise to higher levels of volatility, as there is both social interaction and conformity behavior and the market is liquid enough to absorb the different types of orders of the different groups of investors.

In the second series of experiments, we will investigate the effect of heterogeneity in the agent population on the stock market volatility. In real stock markets, investors may differ in their perceived risk of investing and therefore have different levels of confidence. This heterogeneity may act as a compensating force vis-à-vis the stock market volatility. In a heterogeneous stock market, the chances that the trades of a very optimistic investor match those of a very pessimistic investor and compensate each other are greater. In this experiment, heterogeneity is defined as a uniform distribution between the minimum and the maximum level of C. The greater the distance between the minimum and maximum level, the greater is the heterogeneity of the stock market. When we increase the heterogeneity of the stock market population, while keeping the average level of C constant, we can observe a decreasing volatility. In practice, this is done in the following way. We will first set both the "ConfidenceMax" and "ConfidenceMin" at the same values, e.g., 0,55, to simulate a homogenous stock market. Then, we perform a number of experiments, in which we keep the average level of C the same (0,55), but vary the bandwidth of C. When one chooses to use C (0,55) as a benchmark, one subsequently sets the "ConfidenceMax" and "ConfidenceMin" at (1,0-0,1), (0,9-0,2), (0,8-0,3) and so forth. After the experiments, one again opens the log files and reads them in into a statistical program to generate the graphs.

In the third series of experiments, we will investigate to what extent the simulation generated macro level data match those of real stock markets. In order to do this, one should start with performing an empirical study into micro level investor behavior and use the results of this study to set the model parameters at empirically valid levels. Subsequently, one performs a series of simulation runs, and saves the macro level data. This data can then be compared to the data of a representative real world stock market by using e.g., a GARCH (1, 1) analysis. A number of caveats apply, however. First, the empirical period that is used as a benchmark should be representative for the situation as simulated. That is, one should not compare e.g., a very tranquil market situation as could be observed for example in Japan in the 1990s of the former century, with simulation generated data that are the result of a parameter setting that represents a very volatile market inhabited by investors with low confidence who are susceptible to herding processes. Second, one should take care that the frequency (hourly, daily, or weekly) of the benchmark data is comparable to the frequency of the simulation generated data.

4. Future research questions

Our research approach can contribute to any research program in which the objective is not only to increase the understanding of (1) a micro level phenomenon or (2) a macro level phenomenon, but rather to increase the understanding of the link between these two separate, but always connected, research levels in addition to a thorough understanding of both levels individually.

Our SSE simulation model is capable to contribute to any research program in which research questions are dealt with in which both an increased understanding of micro level investor behavior, macro level stock market dynamics and the interplay between these two levels is wished for. More specific, apart from the possible applications that were discussed in the previous section, one could think of the following specific application area's and this is where our future work interest resides:

- The effect of different network structures on (1) micro level investor behavior, (2) macro level stock market dynamics, and (3) the interactions between these two levels.
- The effect of different positions of individual investors in the social network on the returns of these investors.
- The effect of differences in the weighing of the different possible investment strategies of investors on their individual returns.
- The effect of differences in (1) the way and (2) the frequency with which news enters the stock market on (1) the returns of individual investors in different positions of the social network and (2) the overall stock market dynamics.

The greatest challenge however, is not so much to realize that investors like John Smith (1) really exist and (2) might be more omnipresent than expected, but to discover in what situations the investment behavior of John does not only feel familiar and seems to be sensible, but also leads to positive returns. When John realizes that his investment behavior is not abnormal, but perhaps suits one situation better than another, he can truly be reassured when wishing his wife and newborn child goodnight.

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Endnotes

[i] We assume that the objective risk (the standard deviation of returns) of an investment is equal for all investors. However, due to individual differences between investors with regard to their investment related knowledge and experience, investors may differ with regard to the perceived risk of an investment. This leads to differences in the confidence that individual investors have in their own expectation about the next period's value of a stock. In the remainder of the paper, when we distinguish between investors with higher and lower confidence, we assume that investors with higher confidence perceive less risk and investors with lower confidence perceive more risk due to e.g., differences in investment related knowledge and experience.

[ii] This in contrast to research which assumes fully informed investors who refrain from searching for information in their social network.

[iii] Tom Tom is a leading brand of portable navigation equipment headquartered in The Netherlands.

[iv] See e.g., www.simstockexchange.com for more information on the model and the possibility to download a demonstration version of the model.

[v] After running the executable file version of the SimStockExchange, a folder called "logs" is automatically created in which both the stock prices and the returns are logged as text files. These folder is created in the same folder from which the executable file version of the SimStockExchange is executed.