Towards modelling traders' behavior

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Towards a Fuzzy Model of Traders' Behavior
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Towards a Fuzzy Model of Traders' Behavior

1. Introduction
A large part of understanding financial markets and the ways in which prices converge towards certain values resumes to understanding the ways in which traders act. Comprehending the behavior of traders should lead to a better understanding of price forming processes and, most importantly, superior design of artificial agents meant to function in highly dynamic environments such as financial markets. Our current research focuses on developing a model of the behavior of traders that will enable better investment decisions at machine-level while significantly reducing the need for human intervention to such an extent that the latter becomes unnecessary.

The approach employed towards achieving this goal, developing an artificial trader, involves three stages, mainly due to the complexity of the problem being addressed. The first two stages focus fully on gathering expert knowledge by exploring the space of variables available for making investment decisions (stage 1) and then trying to achieve more in-depth knowledge and a more quantifiable representation of the variables involved (stage 2). During the final stage (stage 3) the gathered expert knowledge will be exploited towards the actual development of an appropriate model underlying the actions of the artificial trader. The approach taken for the gathering of relevant data on traders' behavior during the first two stages is by means of interviews with the traders themselves. This approach has not only been chosen due to its highly practical nature, but also due to the opportunities of gathering data in an alternative way – by observing (most of) the interviewed traders during their daily trading activities. Currently, stage 1 of the research has been completed and steps are being undertaken towards completion of the second stage.

This document reports on the stage 1 findings based on [1] and the outlook they offer towards the modeling of traders’ behavior. The choice for the way in which this will be modeled has fallen on fuzzy systems, mainly due to the capacity of the latter of representing human domain-knowledge. This document also presents the motivation behind this choice more broadly together with the first steps that need to be taken towards the fuzzy modeling of traders’ behavior based on the stage 1 findings.

The outline of this document is focused around the stage 1 approach and results, and on the perspective offered by these results towards the development of a fuzzy model of traders’ behavior. Section 2 gives an overview of the available scientific literature on modeling traders’ behavior. Section 3 describes the
approach taken during the first stage of the research, with a focus on the questionnaire employed for the purpose of data gathering. In the fourth section, the answers given by traders’ to this questionnaire are presented in an aggregate way, thus not focusing so much on the individual answers but on the general image they offer. In the fifth section, an attempt is made at defining in big lines the possible architecture for a fuzzy system resembling traders’ behavior. Next, in section 6, a few conclusions that can already be drawn from the current research are presented and finally, in section 7, the ideas for further research are mentioned and briefly discussed.

2. The Behavior of Traders in Scientific Literature

Although the available literature on the beliefs and behavior of traders often refers to a specific sector, time horizon or asset, it still is a good starting point for this study. First of all, previous literature supports a broader view on the context of the influences on trading decisions, starting from the Efficient Market Hypothesis (EMH) to the field of Behavioral Finance and finally to the specific factors upon which traders make their decisions. Second, more important, this study can build on the set up, conclusions and discussions of related research. At the end of this chapter a brief summary is presented with the main conclusions from previous literature, which has been a basis of this study.

Gooding is one of the first researchers who published a paper on behavioral trading supported by empirical evidence, i.e. a questionnaire to investment professors, portfolio managers and individual investors [3]. To determine the differences between the type of investors, Gooding focused mainly on fundamental financial ratios and technical analysis as influences for trading decisions, such as dividend yield, five-year return on capital, price to earnings ratio and the volatility.

Dhar and Goetzmann carried out a study [4] by means of a survey to test if the EMH existed for stock investors in the telecom sector during the ‘Internet Bubble’. This is especially interesting, because now looking back we are able to see that stock prices at that time deviate much from their actual value. This helps us understand the results of mass psychological trend behavior. Dhar and Goetzmann found that a large number of investors took actions contrary to the EHM. Many of them believed to have the capability to recognize disvalued assets upon own research or advice of a broker.

In the paper ‘Difference of Opinion Make a Horse Race’ Harris and Raviv [5] describe a model of trading in speculative markets developed on the differences of opinion amongst traders. Although this model only takes into account price and volume and is restricted to the risk preferences of traders, it demonstrates that traders share common beliefs but differ in the way they interpret the information. Barber and Odean [6]
continued in this field and studied the beliefs of traders more in-depth on a psychological level. They address quite well that heterogeneous beliefs are needed to generate significant trading.

An extensive study in the macroeconomic implications of the beliefs and behavior of foreign exchange rates conducted by Cheung and Chinn, reports four conclusions. First, 30% of the traders are best characterized by technical trading. Second, news about macroeconomic variables is rapidly incorporated in the exchange rate. Third, interest rates seem to be always important, while other individual macroeconomic factors are more important over a longer time horizon. Finally, economic fundamentals are important at longer time horizons. Cheung and Chinn have carried out a survey under 142 currency traders among the larger financial institutions. They have categorized these traders into technical trading, fundamental trading, customer order and jobbing. Jobbing is described as a trading style in which the trader continuously buys and sells in order to make money profits in perhaps small increments [7]. Lien [8] supports the paper of Cheung and Chinn by advocating that traders should consider both schools of thought, i.e. technical and fundamental analysis as support for trading decisions.

The MainStay Investment Group has performed multiple studies to assess the impact of external shocks (e.g. wars, natural disasters) on the S&P 500, which is widely regarded as the best single gauge of the U.S. equities market. This index includes a representative sample of 500 leading companies of the U.S. economy; hence it can be seen as a good representation of the total market. They present the results of the impact of hurricanes within one month, 3 months, one year and three years on the S&P 500 [9]. Uncertainty from hurricanes (generalized to natural disasters) can have a sudden drop in value on the S&P 500, i.e. traders are influenced by natural disasters in their decision making. To determine the factors which influence trading decisions, a structure based approach is necessary [3, 4 and 7]. On basis of previous literature as well as common sense this study has categorized the factors into six categories, respectively fundamental financial, technical analysis, global, psychological, monetary and external asset factors. For each of these factors multiple variables have been selected to include in this study. Furthermore previous literature has demonstrated that studying the beliefs and behavior of traders can best be carried out by means of empirical evidence, i.e. interviewing traders. This study also pursues this idea and makes use of a questionnaire to gather empirical data in the first stage of the research.

3. Data Collection on Traders’ Behavior
The data gathering in the first stage is quantitative in nature and consists of a questionnaire. The employed questionnaire contains a total number of 23 variables organized under six factors: External Asset Factors, Fundamental Factors, Monetary Factors, Global Factors, Psychological Factors and
Technical Analysis Factors respectively. A total of eight traders have been approached with this questionnaire and each of the interviewed traders had to indicate, on a scale from 1 to 5, the importance of each of the 23 variables in his own decision-making.

![Figure 1: The three dimensions of a trader](image)

4. Analysis of Trader Data

This section reports on the first stage findings and the conclusions they bring to light. As outlined in the previous section, the traders have rated the list of 23 variables on a scale from 1 to 5. Based on these ratings the variables can be ranked according to their total ratings. The total rating of a variable for a
specific level of importance, say 5, is calculated as the total number of traders that have rated the specific variable a 5 divided by the total number of traders that participated in the study. In order to determine the ranking of the variables, the list is first sorted in descending order based on the total ratings for level 5. The same procedure is then repeated for each level of importance, ending with level 1. The most important 25% of the variables as rated by the traders that have participated in this study are presented in figure 2.

The results obtained by means of the stage 1 questionnaire, and especially the 25% most important variables, give a good indication of the emphasis of the following stages. A better understanding of what is meant with for example own risk profile will most likely be crucial towards modeling traders’ behavior. The numbers obtained also give a first indication of the fuzzy rules that might be employed and on where the focus should lay in the following stages of the research. For example, one might want to find an average opinion on how the variable volume can influence prices and, more importantly for the current research, the traders’ decision making. While keeping in mind the purpose of defining fuzzy rules based on this variable, the interviewer should try to establish how exactly this variable has an influence on the individual trader’s decision making and, ideally, try to quantify this influence. This idea can be applied to all variables present in the study, while naturally focusing on the most important ones. Another important idea that should be kept in mind when trying to quantify these effects of variables on traders’ decision making is that some of the variables might complex – they might represent an aggregation of more underlying variables, such as might be the case for the most important variable in the study: Own Risk Profile. Moreover, the variables underlying this measure might be different all together form trader to trader, in which case one might consider separately modeling this variable before introducing it in the model. With these thoughts in mind, a first attempt can be made at defining the possible architecture for a fuzzy system of traders’ behaviors.
5. Towards a Fuzzy Model of Traders’ Behavior

Fuzzy logic, the foundation of fuzzy systems, offers the means to express human domain knowledge in a more realistic, accurate way, that is, allowing for the ambiguity typical to humans. Unlike binary logic that is crisp in nature allowing for only two states, fuzzy logic is more versatile in expressing gradations. It does so by employing fuzzy descriptors such as for example “strong” and “high” [2]. Mainly due to these properties, fuzzy logic seems like the appropriate choice to model trader knowledge and trader behavior. The quantification of the variables playing a role in traders’ decision making, as well as their effects on the ultimate decision, will most likely not be a crisp number, but will be expressed as a linguistic variable rather than a numerical one.

Input

The main purpose of the first two stages of the current research is to identify the different variables that play an important role in the trader decision making process and to quantify their effect. Having identified these variables, the problem of deciding upon the input of the system becomes much simpler. A sensible choice could be to consider the top 25% of the variables (ranked on importance) and use these as an input. Building upon the first stage results, and more exactly on the top quarter variables as presented in Figure 2, it is possible to distinguish between two main categories of variables: observable and deducible. Observable variables are variables that can be observed and easily quantified in a straightforward manner. Examples of such variables are volume and macroeconomic variables. However, some variables that are highly relevant in the current context, such as wars / terrorist attacks, cannot be observed/quantified directly. These variables can be modeled, and their value, and thus also their impact on the final trading decision, can be “deduced” indirectly, from these other variables on which they depend. In the remaining part of this section the focus will be on the most important 7 variables as identified in the first stage of research and on the issues concerning each of them in the context of inputs to a fuzzy model for traders’ behavior.

Own Risk Profile

This variable refers to the risk profile of the trader himself, and is used to indicate how risk adverse (or not) a trader is, i.e. how much risk the trader is willing to take in maximizing his returns. Even though playing an important role, this variable can only be modeled in case traders or at least groups of traders share similar risk attitudes.

Wars / Terrorist Attacks & Natural Disasters

These two variables are difficult to model only after the first stage of the research. In the case of natural
disasters for example, other variables play an important role, variables such as: nature of the disasters, location, strength, etc. These two variables and the precise way in which they affect trader decision making will be investigated in the next stage (stage 2) of the research.

**Raw Materials**

Identified as the fourth most important variable, prices of raw materials (or prices of the other raw materials in case of commodity traders) are also one of the easiest to observe and quantify. The prices of raw materials can directly be used as input in numerical form.

**Intuition**

This is probably the most difficult variable to quantify and model. In order to achieve this, a number of assumptions could be made, and this will most likely also be done in the current case. For example, intuition (in the vision of deducible variable) could be regarded as mostly based on experience, and modeled as such. Learning from experience (i.e. past, history) may in its turn be modeled as a neural network generating expectations on prices, based on historical data. The expected price differential could then be used as input for the fuzzy system modeling traders’ behavior.

**Volume**

Another easily observable and quantifiable variable, volume can be used directly as a numerical variable.

**Macroeconomic variables**

Macroeconomic variables such as inflation, interest rates and unemployment can, upon a more precise identification of their importance, be used as numerical inputs indicating the current levels of these variables or the difference between the current level and the level in the previous time period.

**Rules**

Extracting more precise expert knowledge on the way trading decisions are made by human traders is the focus of the second stage of research. This step is also the one that underlines the most the added-value of using fuzzy systems in the attempt to model traders’ behavior, as the information that will be obtained upon the interviews with traders will most likely be expressed in an ambiguous way. For example, a rule such as “IF Volume is High and Price is decreasing THEN Strong Sell”. Such knowledge would be very difficult to express by employing other tools for modeling, while in fuzzy systems this comes almost naturally.
Output
The output of the system should be in the form of recommended actions, such as “strong buy”, “hold”, etc. The actions that the system recommends will also form the basis for benchmarking its performance. This can be quantified as the excess return obtained by following the system advices when compared to an appropriate benchmark.

6. Conclusions
The results of the stage 1 analysis form a good basis towards a better understanding of the way traders behave. These results also provide a first insight into how to develop a fuzzy system able to accurately simulate the behavior of traders. Even though variables such as intuition seem difficult to model, the combination of assumptions together with a better understanding of what is actually meant by such concepts should provide satisfactory solutions towards quantifying this type of variables. But most importantly, the stage 1 results provide for the foundation of the next stage of research, in which a more qualitative approach will be taken towards understanding the behavior of traders. The first attempt at describing a fuzzy system for modeling traders’ behavior also provides a number of issues on which the focus should fall in the second stage, and resolving these should ensure the successful development of a system closely resembling the behavior of traders.

7. Further research
The quantification of the importance of the different variables offers interesting perspectives for both stage 2 and stage 3 of the research. The emphasis of the more in-depth approach of stage 2 will be on better understanding how the top 25% of the variables as presented in figure 2 influence traders’ decision making. The focus of this second stage will also fall on better comprehending these variables, and the way in which they are observed by traders. Additionally, the first stage results offer a more specific perspective on the third stage of the research, the actual development of an appropriate model that underlies the actions of the artificial trader. As described in the previous sections, fuzzy systems offer what seems the most feasible solution towards modeling traders’ behavior and in the third stage of the research the focus will fall on further developing and implementing the architecture described here, thus providing a fuzzy model of traders’ behavior.
References


