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## Article

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Arab Economic and Business Journal

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*Suggested Citation:* Dhaoui, Abderrazak; Khraief, Naceur (2014) : Sensitivity of trading intensity to optimistic and pessimistic beliefs: Evidence from the French stock market, Arab Economic and Business Journal, ISSN 2214-4625, Elsevier, Amsterdam, Vol. 9, Iss. 2, pp. 115-132, <https://doi.org/10.1016/j.aebj.2014.05.008>

This Version is available at:

<https://hdl.handle.net/10419/187522>

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## Conference Title

# Sensitivity of trading intensity to optimistic and pessimistic beliefs: Evidence from the French stock market

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## ARTICLE INFO

### Article history:

Received 20 December 13

Received in revised form 16 March 14

Accepted 09 May 14

### Keywords:

Trading intensity

Market trend

Animal spirits

Fuzzy logic

## ABSTRACT

In this paper, we will offer some evidence indicating that investor sentiment plays a central role in explaining trading intensity and market trend changes. Based on both econometric and fuzzy logic approaches, the empirical findings show that pessimistic sentiment has a particularly significant impact on the French financial market trend. Moreover, the results suggest that the impact of pessimism on asset returns exceeds that of optimism as a direct indicator of investor's beliefs. Indirect indicators of agent sentiment present more smoothed effects on these two market components. Our results indicate that incorporating psychological factors in macro-financial models leads to better supervision and control of the main drivers of the markets.

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## 1. Introduction

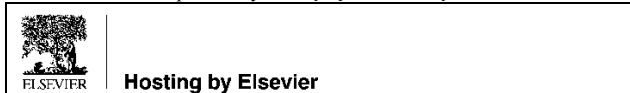
Although there are many studies supporting the Rational Expectations Hypothesis in financial markets, the incorporation of psychology to financial theory stills relatively a new area of research. Baker and Nofsinger (2002) note “*proponents of behavioral finance contend that people may not always be ‘rational’, but they are always ‘human’.* Thus,

*behavioral finance exposes the irrationality of investors in general and shows human fallibility in competitive markets*”. Recently however, psychological components have come to the forefront of academic research, and this probably because of the financial crises and recessions that emerged and for which the hypothesis of rationality failed to find convincing evidence. The evidence in fact suggests that behavioral factors always play a central role in financial markets. Over the last two decades many recent studies such as Haruvy et al., (1999), Barberis et al., (1998),

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Peer review under responsibility of Holy Spirit University of Kaslik.



Akerlof (2009), Guldberg and Shiller (2010), emphasize psychological factors in explaining financial crisis.

Not all the investors are rational and their demand for risky assets is influenced by their beliefs or sentiments. Optimism, pessimism and overconfidence help determine how in-depth the decision-making process can be changed over the time. Baker and Wurgler (2006) show that when agent sentiment is high (low) for stocks that are hard to value or arbitrage; they tend to earn relatively low (high) subsequent returns. The aim of this paper is to examine the relationship between investor sentiment on one hand, and the trend of trade and its intensity on the other hand. One of the most important issues investigated is the sensitivity of investors' behavior to their feelings and beliefs. In other words: *How do investors' sentiments and beliefs influence their investment strategies?* We aim to analyze how the investors' belief impacts the trading behavior in financial markets and in what degree the market trade and the trading intensity are sensitive to investors' beliefs and sentiments.

We use econometric and fuzzy logic approaches to investigate the sensitivity of both market trend and trading intensity on the investors' beliefs. The use of the fuzzy logic approach is motivated by the need for supervising of the investors' sentiments and beliefs evolution. The optimism as a positive sentiment can be built over the time, but can be broken after a single shock. Since sentiments are not explicitly supervised due to their fuzzy nature, classical econometric models are not suitable for a good prevision. Fuzzy logic approach is oppositely more appropriate to predict the relationship type between unobservable variables. This technique was been used in Hachicha et al. (2011) to control the fuzzy complementarity between the fundamentalists and the behaviourists in the explanation of financial market dynamics. The authors attribute the use of this approach to the difficulty of prediction due to the complexity and the behavior of traders. In the same way, Bekiros (2009) used a fuzzy approach to investigate the decision making of rational investors in speculative stock markets and the trading strategies with behavioral approach. Dhaoui et al. (2013) used the same approach to investigate how human psychology drive economies and markets. They document that the fuzzy logic controller constitutes one of the most effective methodology that allows controlling the sensitivity financial market component (trading volume and stock returns) to behavioral variables such the investors' feelings and sentiments.

Earlier studies have predicted the sentiments and beliefs impacts only theoretically. We believe our work is an important first step to an empirical validation of the behavioral macroeconomic model with non-observable investors' characteristics.

This paper contributes to the behavioral financial literature on how investor sentiments (optimism, pessimism, overconfidence) impact stock price movements, and it does so using French data and fuzzy logic techniques. Our results seem to confirm a fuzzy relationship between these variables. The remainder of this paper is organized as follows: Section 2 presents a literature overview on investors' sentiments and beliefs. Section 3 deals with the description of data and the new fuzzy methodology implemented. In section 4 we present and discuss the major results, while section 5 concludes.

## 2. Literature Review

The Efficient Market Hypothesis assumes that there is perfect information in the stock market and that the investors are rational decision makers. However, by the start of the twenty-first century a new stream of financial literature emerged advocating that stock prices depend on psychological and behavioral factors. In that, the *behavioral finance* approach has quickly become the dominant model for understanding the variation of stock prices.

Behavioral finance incorporates psychological components to counteract the widely advocated rationality in conventional finance. Investor sentiment was introduced as a relevant factor that significantly influences the financial market behavior. The basic idea behind this approach is that human nature includes both rationality and animality and the latter has more significant effect on investor behavior than the former. Keynes was the first to suggest that emotions can influence human behavior instead of rational processes. In his book "*The General Theory of Employment, Interest, and Money*", Keynes introduced the term "animal spirits" as "*a spontaneous urge to action rather than inaction*" to explain the economic realities. He states specifically that "*most, probably, of our decisions to do something positive, the full consequences of which will be drawn out over many days to come, can only be taken as the results of animal spirits [...] and not at the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities*".

In the same way as Keynes (1936), Akerlof and Shiller (2009) suggested the incorporation of "animal spirits" to macroeconomic models. They argue that "*it is necessary to incorporate animal spirits into macroeconomic theory in order to know how the economy really works. In this respect the macroeconomics of the past thirty years has gone in the wrong direction. In their attempts to clean up macroeconomics and make it more scientific, the standard macroeconomists have imposed research structure and discipline by focusing on how the economy would behave if people had only economic motives and if they were also fully rational.*"

Akerlof and Shiller (2009) describe different aspects of "animal spirits" such as corruption, money illusion, stories, exuberance and overconfidence (Akerlof and Shiller (2009), Guldberg (2010). Moreover, other authors suggest that there exist additional factors in order to better explain the behavioral and psychological bias on the decision-making process in financial markets. In particular, optimism (Haruvy et al., (1999), Weinstein (1989), Otten (1989), pessimism (De Bondt and Thaler (1987), Barberis et al., (1998), or overconfidence (Daniel, (1998), Hirshleifer and Subrahmanyam (1998) have been shown to affect the financial investment decisions.

Undoubtedly, differences in preferences and beliefs lead to differences in investors' behaviors. Optimistic as well as pessimistic

investors adapt their behavioral trading strategy to their expectations of future risk and return. More optimistic investors suppose that an increase of returns will be followed by another new increase. On the other side, more pessimistic investors suppose that the decrease on return will be followed by a new series of down-trending behavior. Therefore, optimistic investors are more sensitive to returns increase than to returns decrease. In contrast, the pessimistic investors are more sensitive to the returns decrease.

According to theoretical predictions (Hayes (1998), Jackson (2005), Beyer and Guttman (2011), trade demand is asymmetrically responsive to optimistic versus pessimistic analyst earnings forecasts. In expense to these forecasts we suppose that both optimistic and pessimistic investors react differently to an increase or a decrease in price. The more the investor is optimistic the more her trading volume increases. In fact, the optimistic investor expects an increase on prices because she predicts that this increase will be followed by a new price increase, which allows her to realize future gains. On the other side, when prices decrease the investor continues to trade normally since she is less sensitive to negative results. In a similar way, the more pessimistic investors expect that a decrease of prices will be followed by a new series of decreases; as a result, they reduce their trading volume to avoid potential losses. However, since they are less sensitive to positive results, the pessimistic investors will trade normally when they expect an increase in future prices.

In the same vein, the empirical evidence supports a significant and positive relationship between price changes and trading volume. Using daily data for both market indices and individual stocks Crouch (1970, 1998) found a positive correlation between the absolute price changes and trading volume. Clark (1973) found also a positive relationship between the square of the price change and aggregated trading volume using daily data. Specifically, optimistic investors' underestimate their exposure to risk and exaggerate their reaction since they expect only positive results and neglect the failure. In the same vein, Shu (2010) being aware of the characteristics assigned to each type of sentiment, argues that optimistic investors are less patient than those who are more pessimistic and react aggressively by underestimating their exposure to risk. Instead, the more pessimistic investors display a high-level of risk aversion. They become more and more receding when they make a decision to invest in risky assets which leads to a decrease in trading volume. Chuang, Ouyang and Lo (2010) use a weekly data during the period January 1990 - December 2004 to supervise the change in investor sentiments in Taiwan Stock Market. They find that the change in trading volume can be used as a proxy for investor sentiments. They argue that a positive deviation of trading volume implies that investor sentiment jumps to become more optimistic and vice-versa.

For the French stock market, Rousseau, Germain and Vanhems (2008) argue that pessimistic investors decrease their trading volume and avoid risky assets to prevent a loss. Psychological literature assimilates the pessimism to a statement of impotence or to an absurdity of human existence. Alongside, the authors find that optimistic investors increase their trading volume and invest more in risky assets waiting for a higher yield in the future.

Carver, Scheier and Segerstrom (2010) suggest that optimism and pessimism sentiments focus on expectancies for the future and the way that the investors confront problems. The authors find that optimistic investors face adversity differently than pessimistic ones. They presume

that optimistic investors use more adaptive ways and "commit" to cope with the worst scenarios. In contrast to optimism, pessimism refers to fear, doubt and stress, in that pessimistic investors tend to be hesitant and doubtful in the face of different challenges. All these empirical findings lead to the conclusion that investor sentiment constitutes an important factor that determines the trading volume and investment strategies.

### 3. Data and behavioral indices

A recent study showed that the French were among the most pessimistic people in the world; hence the French Stock Market was a suitable choice for our study. French data are more ideal since for controlling the influences of investor sentiments and beliefs. The French population is prone to be the most pessimistic all over the world\*. The optimism, as a positive sentiment, can be built over the time, but can be broken after a single shock; investors will be more sensitive to pessimistic aspects than to optimistic aspects. Based on this argument the most appropriate data to supervise the investors' sentiments remained that reflecting the dominant characteristic which is the pessimism in investor sentiment. The data sample includes individual daily stock prices and trading volumes on the CAC40 Stock Index between January 2005 and December 2011. The analysis also required the construction of aggregate data. The output variables include returns and trading volume of the CAC40 index. In order to determine the input variables we need to use individual prices and returns to calculate their average and conditional measures.

According to the behavioral finance literature "animal spirits" create waves of optimism and pessimism. The Optimism about a given asset is occurring when expected prices increase abnormally. However, pessimism takes place when investors estimate a dramatic decrease in prices. There are two direct analytical methods for measuring investor sentiment. An optimistic investor expects an above average stock price level at any given time. She becomes pessimist when the price falls below the average level. Then, the average of individual stocks is used to calculate optimism and pessimism variables of CAC40 Stock index. We report a strong evidence of optimistic behavior when individual stock price increases abnormally. Considering the aggregate market, the average of conditional absolute price forms the best measure of optimism sentiment. The investor reacts as an optimist if she realizes that the price increase over the medium level. Then, giving the conditional expectations, optimism about the stock price will be calculated as follows:

$$Opt_t = \frac{1}{N} \sum_{i=1}^N (P_{it} | P_{it} > E[P_i]) \quad (1)$$

where,  $P_{it}$  represents the price of the stock  $i$  at the time  $t$  and  $E[P_i]$  the mathematical expectation of price series of the stock  $i$  at the time  $t$ .

\* According to the interview realized by the « Gallup International Association » for the journal "Le Parisien" for the years 2011 and 2012, the French population constitutes the most pessimistic population all over the world. For more details see: [http://www.lexpress.fr/actualites/2/les-francais-champions-du-monde-du-pessimisme-en-2011-selon-bva\\_949381.html](http://www.lexpress.fr/actualites/2/les-francais-champions-du-monde-du-pessimisme-en-2011-selon-bva_949381.html) ; <http://www.lefigaro.fr/international/2011/01/03/01003-20110103ARTFIG00628-les-francais-champions-du-monde-du-pessimisme.php> ; [http://www.lexpress.fr/actualites/1/societe/55-des-francais-pessimistes-pour-2012\\_1067011.html](http://www.lexpress.fr/actualites/1/societe/55-des-francais-pessimistes-pour-2012_1067011.html)

$$E[p_i] = \frac{1}{T} \sum_{t=1}^T p_{it} \tag{2}$$

$N$  is the number of individual stock in the French CAC 40 stock market index. We use the inverse of the absolute value since more the stock prices are lower more likely the investors are pessimistic. A positive correlation observed between the standard price and the trading volume suggests a negative effect of pessimistic investor on the trading volume. To avoid certain opposite effects we propose using the inverse of the pessimism measurement. Therefore, giving the conditional expectations, this index is calculated as follows:

$$Pes_t = \left[ \frac{1}{N} \sum_{i=1}^N (P_{it} | P_{it} < E[P_i]) \right]^{-1} \times 100 \tag{3}$$

Investor sentiment about stock prices can also be controlled by using the following factors:

$$Sent_1 = ID_t = \frac{APSV_t}{DPSV_t} \tag{4}$$

where  $Sent_{1t}$  is defined as the Increase vs. Decrease in stock price at the time  $t$ ,  $APSV_t$  represents the number of securities that experience a price increase at the time  $t$ , and  $DPSV_t$  the number of securities that know a price decrease at the time  $t$ . Similarly,

$$Sent_2 = NIND_t = \frac{NAPSV_t}{NDPSV_t} \tag{5}$$

where  $Sent_{2t}$  represents new increases vs. new decreases in stock prices at the time  $t$ ,  $NAPSV_t$  defines the number of new securities that experience a price increase at the time  $t$ , and  $NDPSV_t$  denotes the number of new securities that show a price decrease at the time  $t$ .

Market Trend (MT) gives a signal for investors' decision: "BUY", "SELL" or "Hold". The MT can be defined as the ratio of the difference between the closing price and the lowest one observed over the latter  $x$ -days to the difference between the highest and the lowest prices noticed over the latter  $x$ -days. Considering weekly analysis time unit we set  $x$  equal to the number of trading day per week, that is  $x$  equal to 5. Therefore, using the aggregate prices of CAC40, the MT can be written as follows:

$$MT = \frac{Closing Price_t - Lowest Price_{(t,t-5)}}{Highest Price_{(t,t-5)} - Lowest Price_{(t,t-5)}} \tag{6}$$

We use the trading volume as a proxy for trading intensity (TI). Investors increase their trading when they expect an increase of prices (optimistic sentiment). However, the trading volume decreases, if they expect the prices to go down. Using aggregate data, this variable is computed as follows:

$$TI = Ln(Trading Volume) \tag{7}$$

#### 4. Investor beliefs and sentiments: Econometric and Fuzzy analysis

In the first step we try to control the sensitivity of MT and TI against the investors' beliefs and sentiments (Optimism, Pessimism,  $Sent_1$ ,  $Sent_2$ ) using econometric modeling based on a SUR estimation.

$$\begin{cases} TI_t = \alpha_0 + \alpha_1 Opt_t + \alpha_2 Pes_t + \alpha_3 Sent_{1t} + \alpha_4 Sent_{2t} + \\ MT_t = \beta_0 + \beta_1 Opt_t + \beta_2 Pes_t + \beta_3 Sent_{1t} + \beta_4 Sent_{2t} + \end{cases} \text{(Model 1)}$$

$TI_t$  : represents the Trading Intensity at time  $t$ ;

$MT_t$  : represents the Market trend at time  $t$ ;

$OPT_t$  : represents the investor Optimism indicator at time  $t$ ;

$PES_t$  : represents the investor Pessimism indicator at time  $t$ ;

$Sent_{1t}$  : represents the first indicator for the investor sentiment at time  $t$ ;

$Sent_{2t}$  : represents the second indicator for the investor sentiment at time  $t$ .

The results in Table 1 show on average that the number of stocks that experiences an increase in prices is quite higher than that of stocks that experiences a decrease. The number of new stocks realizing an increase reaches about more than three times the number of new stocks in which a decrease is observed. The number of new stocks having an increase exceeds by about 1.8 times the number of new stocks having a decrease. Furthermore, MT is very centralized nearly to its average level. The number of stocks having less MT is very important compared to the number of stocks having a high MT. However the TI is centralized on average nearly its maximal level. The differences between the average and both the maximal and the minimal level reach respectively about 1.31681 and 2.43039. The optimism and pessimism of investors are quite weak. They are centralized on average around their minimal levels. By construction, the market trend is a transformation of the stock returns. Moreover, the evolution of the trading intensity depends substantially on the evolution of stock returns. For these reasons, the MT and TI seem to be apparently unrelated however; they are related across their residual terms. Thus a seemingly unrelated regression is appropriate to estimate the multi-equation model presented above (Model 1). The estimation of a simultaneous multi-equation model requires that this model is overidentified. One model can be overidentified if each of his equations is at least just-identified. To examine the overidentification of our multi-equation model we denote  $W$  as the number of endogenous variables included in the model;  $W'$  is the number of endogenous variables included in the equation;  $K$  the number of exogenous variables included in the model;  $W''$  the number of exogenous variables included in the equation. If there is any restriction in each of the model equations, an equation is qualified to be overidentified if  $W - I \leq W' + K - K'$ . In our case, since  $W - I = W - W' + K - K'$  for each equation, the model is mainly overidentified. Thus, a two-stage-least square estimation is more appropriate in particular a SUR estimation is recommended. Table 2 presents the results for SUR estimation of the regression of TI and MT on beliefs and sentiment indicators using two least square methods.

The results in Table 2 show that both MT and TI are significantly sensitive to optimism. However, while the effect is positive on the MT it is oppositely negative on the TI. This indicates that optimistic investors react by decreasing their trading when the MT shows favorable evolution of returns waiting for better results in the future. Also, the pessimism is positively related to both MT and TI. When stock index experience favorable tendencies, pessimistic investors express worries on future unfavorable evolution of returns and thus liquidate their positions in

increasing their sell-trading.  $Sent_1$  and  $Sent_2$  exert only significant effect on the Market Trend. The trading intensity is not significantly sensitive to these sentiment indicators. Investors react following their beliefs and withdraw the individual stock characteristics as indirect sentiment proxies.

Even though the results show statistical significance, the sensitivity of TI and MT on optimism and pessimism indicators as well as the indicator of the last evolution that stocks experience, remains questionable. In fact, when results indicate positive (negative) reaction of TI to the pessimism (optimism), we cannot judge if this increase (decrease) is due to a sell or another strategy. To find an answer to this problem, a fuzzy control system is introduced. It allows investigating with more preciseness the evolution of TI and MT following the variations of the investors' beliefs and sentiments. To explore the relationship between MT and TI on one hand and the indicators of beliefs and sentiments (Opt, Pes,  $Sent_1$  and  $Sent_2$ ) on the other hand, we present in the remainder of this section a fuzzy model in an attempt to support and/or challenge the econometrical results presented in Table 2.

Fuzzy logic as a branch of artificial intelligence was introduced for the first time in 1965 by Zadeh (1965). It deals with reasoning algorithms used to emulate human thinking and decision making. These algorithms are used when process data cannot be represented by classical logic. For example, when investigating the level of information that an investor withholds, in classical logic there is a double sided result. An investor can be either informed or uninformed. There is no an intermediate position. However, the fuzzy logic analysis includes all intermediate positions. Not only extreme values are considered, but also the whole range between the two extreme values will be included. The investors can be uninformed or quite informed or informed. In this paper we introduce a Fuzzy control model that includes four input variables. For each input we attribute three belief intervals: High, Medium, and Low. After defuzzification, two output variables are controlled. Following the fuzzy logic process (IF-THEN), the model takes the form depicted in Figure 1.

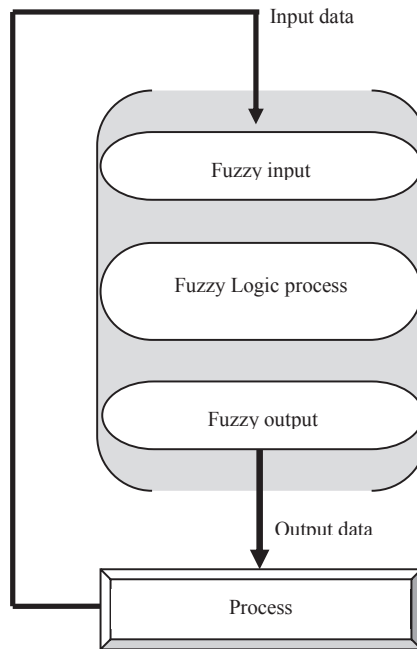
**Table 1- Summary statistics for dependent and independent variables.**

Statistics	Endogenous variables		Exogenous variables			
	TI	MT	Opt	Pes	Sent <sub>1</sub>	Sent <sub>2</sub>
Mean	14.95998	0.738998	2.601749	2.92743	1.005945	3.279962
Min	12.52959	0.016847	0	0	0.464206	1.792425
Max	16.27679	4.104432	35	34	2.945429	5.847581
Sd	0.357970	0.424101	5.121306	5.47156	0.378252	0.859178
Skewness	-0.81657	2.045383	4.296946	2.91583	1.765905	0.682185
Kurtosis	7.260038	11.58979	24.79376	11.9142	7.719614	2.680998

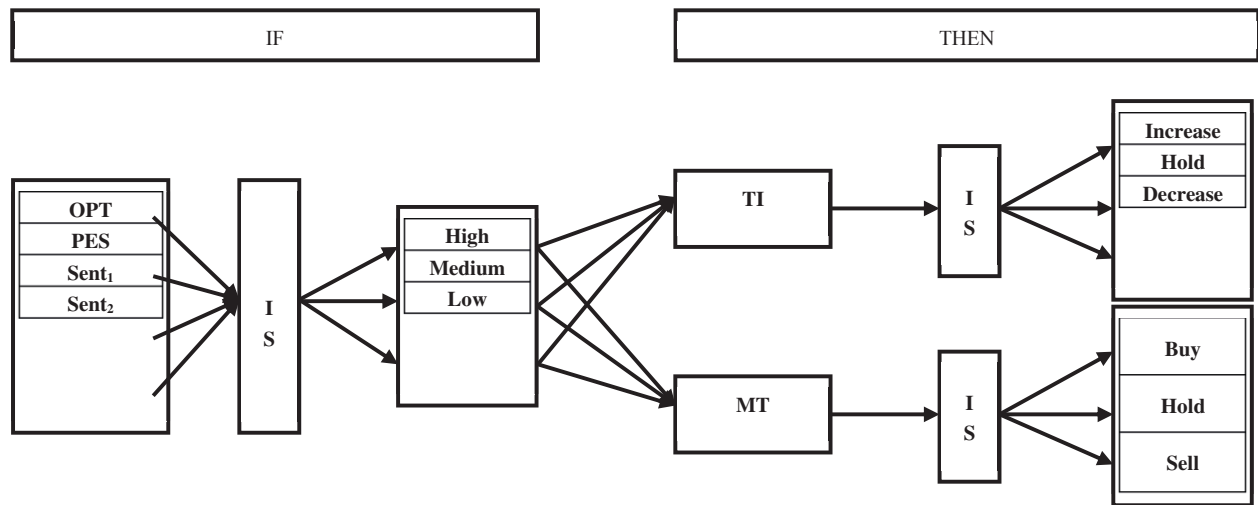
**Table 2- Results for the SUR model estimation.**

	Cons.	Opt	Pes	Sent <sub>1</sub>	Sent <sub>2</sub>	R-Squared	Chi-2
<b>TI</b>	14.88178 (164.01)***	-0.1247673 (3.62)***	0.0617291 (-3.22)***	-0.0019077 (-0.98)	0.0021196 (1.16)	0.0711	120.10 (0.0000) <sup>a</sup>
<b>MT</b>	0.0732104 (0.70)	0.4099946 (9.18)***	0.0874386 (4.45)***	0.0115987 (5.15)***	-0.0217364 (-10.32)***	0.1193	212.38 (0.0000) <sup>b</sup>

Table 2 summarizes the results for the SUR estimation of the regression of TI and MT on beliefs and sentiment indicators. Z-statistics are given into Brackets. \*\*\* indicate the significance level of 1%. *a* and *b* indicate the *p*-values of the *Chi-2* test. TI denotes the trading intensity computed based on the natural logarithm of trading volume. MT measures the Market trend which indicates the investors’ strategy (buy, sell, or hold). Explanatory variables give information about the investors’ sentiments. Opt. and Pes. variables represent direct indicators of optimistic and pessimistic sentiments and feelings of the investors based on their perceptions of the evolution of the stock returns. Sent<sub>1</sub> and Sent<sub>2</sub> give indirect information on investors’ sentiments.



**Fig. 1- Fuzzy logic control system.**



$TI_t$ : Trading Intensity at time  $t$ ;

$MT_t$ : Market trend at time  $t$ ;

$OPT_t$ : investor Optimism indicator at time  $t$ ;

$PES_t$ : investor Pessimism indicator at time  $t$ ;

$Sent_{1t}$ : first indicator for the investor sentiment at time  $t$ ;

$Sent_{2t}$ : second indicator for the investor sentiment at time  $t$ .

Fig. 2- The fuzzy logic model.



Traditional control theory poses that we must at least (i) know the model of the controlled system, (ii) know the objective function formulated in precise term, and (iii) be able to solve the corresponding mathematical problem. If one of these conditions is not satisfied, the traditional methodology will not be applicable. In our case, the model is known, yet the objective function is unknown and cannot be formulated in precise terms since the model includes factors that are related to human nature and behavior which are difficult to be controlled with certainty. Indeed, considering human psychology, an expert cannot usually express his knowledge (beliefs and sentiments) in precise numerical terms but in linguistic terms. Bekiros (2009, 2010) has recently utilized fuzzy logic in economic and financial applications with highly promising results. For our specific model, the knowledge that we extract from an expert can be formulated in terms of rage of optimism, pessimism, overconfidence, and the rationality varying from a low sentiment to a medium and high sentiment. Given these specifications, the fuzzy control methodology presents an important differentiation. The fuzzy logic control system is presented in Figure 2. In this set-up we (i) know the expert’s control rules formulated by words from natural language, and (ii) we produce a precise control strategy. This methodology indeed transforms the informal expert control rules into a precise control strategy. The fuzzy modeling system is the process of formulating the mapping from a given input to an output using fuzzy functions. The mapping then provides a basis from which decisions can be made, or patterns discerned. The fuzzy logic process concerns different steps. Figure 3 summarizes these steps.

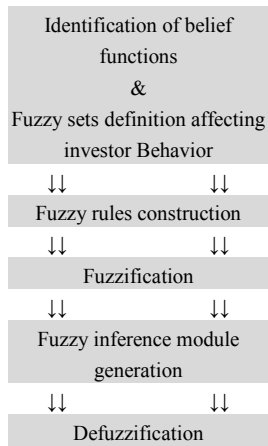


Fig. 3- Steps of the fuzzy logic process.

2.1. Identification of critical factors and belief functions

The specification of the fuzzy logic model requires to define the so-called “belief functions”. We suppose that the investor sentiment can be considered as Low, Medium or High, depending on what the prices are less than a level “a”, belong to the interval [a, b], or are higher than the level “b”, respectively. Based on the continuous uniform distribution and considering “c” as the median of the interval [a, b], the belief function for the fuzzy controller system can be presented as follows:

$$\mu_x(\text{High}) = \begin{cases} 1 & \text{If } P > b \\ \frac{x-a}{b-a} & \text{If } a < P < b \\ 0 & \text{If } P < a \end{cases}$$

$$\mu_x(\text{Medium}) = \begin{cases} 0 & \text{If } P < a \\ \frac{x-a}{c-a} & \text{If } a < P < c \\ \frac{b-x}{b-c} & \text{If } c < P < b \\ 0 & \text{If } P > b \end{cases}$$

$$\mu_x(\text{Low}) = \begin{cases} 1 & \text{If } P < a \\ \frac{b-x}{b-a} & \text{If } a < P < b \\ 0 & \text{If } P > b \end{cases}$$

As indicated in equations 1 and 2 our model includes 2 equations with 4 input variables (OPT, PES, Sent<sub>1</sub>, Sent<sub>2</sub>) and 2 output variables (TI, MT). For the optimism and pessimism input variables, we assume that investors’ beliefs change dramatically following the evolution of stock prices. Considering the change of prices spanning the inter-quartile intervals optimism is considered as Higher when prices exceed the third quartile. If prices are under the value corresponding to the first quartile the variable “Optimism” takes the statue “Low”. Medium Optimism occurs when prices are included into the interval [Q<sub>1</sub>, Q<sub>3</sub>]. Accordingly, the belief function for this variable, and after considering the value Q<sub>2</sub> to control the Medium Optimism, can be computed as follows:

$$\mu_x(\text{High}) = \begin{cases} 1 & \text{If } x > 44.41 \\ \frac{x-5.8}{38.61} & \text{If } 5.8 < x < 44.41 \\ 0 & \text{If } x < 5.8 \end{cases}$$

$$\mu_x(\text{Low}) = \begin{cases} 1 & \text{If } x < 5.8 \\ \frac{44.41-x}{38.61} & \text{If } 5.8 < x < 44.41 \\ 0 & \text{If } x > 44.41 \end{cases}$$

$$\mu_x(\text{Medium}) = \begin{cases} 0 & \text{If } x < 5.8 \\ \frac{x - 5.8}{29.08} & \text{If } 5.8 < x < 34.88 \\ \frac{44.41 - x}{9.53} & \text{If } 34.88 < x < 44.41 \\ 0 & \text{If } x > 44.41 \end{cases}$$

Moreover, the belief function for the "Pessimism" input variable - considering the same evolution of prices into these limits discussed above - can be calculated as follows:

$$\mu_x(\text{High}) = \begin{cases} 1 & \text{If } x < 4.87 \\ \frac{33.64 - x}{28.77} & \text{If } 4.87 < x < 33.64 \\ 0 & \text{If } x > 33.64 \end{cases}$$

$$\mu_x(\text{Medium}) = \begin{cases} 0 & \text{If } x < 4.87 \\ \frac{x - 4.87}{9.07} & \text{If } 4.87 < x < 13.94 \\ \frac{33.64 - x}{19.7} & \text{If } 16.94 < x < 33.64 \\ 0 & \text{If } x > 33.64 \end{cases}$$

$$\mu_x(\text{Low}) = \begin{cases} 1 & \text{If } x > 33.64 \\ \frac{x - 4.87}{28.77} & \text{If } 4.87 < x < 33.64 \\ 0 & \text{If } x < 4.87 \end{cases}$$

In the same way we compute the modalities for the variable Sent<sub>1</sub>:

$$\mu_x(\text{Low}) = \begin{cases} 1 & \text{If } x < 0.18 \\ \frac{3 - x}{2.82} & \text{If } 0.18 < x < 3 \\ 0 & \text{If } x > 3 \end{cases}$$

$$\mu_x(\text{Medium}) = \begin{cases} 0 & \text{If } x < 0.18 \\ \frac{x - 0.18}{0.53} & \text{If } 0.18 < x < 0.71 \\ \frac{3 - x}{2.29} & \text{If } 0.71 < x < 3 \\ 0 & \text{If } x > 3 \end{cases}$$

$$\mu_x(\text{High}) = \begin{cases} 1 & \text{If } x > 3 \\ \frac{x - 0.18}{2.82} & \text{If } 0.18 < x < 3 \\ 0 & \text{If } x < 0.18 \end{cases}$$

$$\mu_x(\text{Low}) = \begin{cases} 1 & \text{If } x < 0.05 \\ \frac{3 - x}{2.95} & \text{If } 0.05 < x < 3 \\ 0 & \text{If } x > 3 \end{cases}$$

$$\mu_x(\text{High}) = \begin{cases} 1 & \text{If } x > 3 \\ \frac{x - 0.05}{2.95} & \text{If } 0.05 < x < 3 \\ 0 & \text{If } x < 0.05 \end{cases}$$

$$\mu_x(\text{Medium}) = \begin{cases} 0 & \text{If } x < 0.05 \\ \frac{x - 0.05}{0.37} & \text{If } 0.05 < x < 0.42 \\ \frac{3 - x}{2.85} & \text{If } 0.42 < x < 3 \\ 0 & \text{If } x > 3 \end{cases}$$

For the TI output variable respectively:

$$\mu_x(\text{Decrease}) = \begin{cases} 1 & \text{If } x < 18.63 \\ \frac{18.98 - x}{0.35} & \text{If } 18.63 < x < 18.98 \\ 0 & \text{If } x > 18.98 \end{cases}$$

$$\mu_x(\text{Increase}) = \begin{cases} 1 & \text{If } x > 18.98 \\ \frac{x - 18.63}{0.35} & \text{If } 18.63 < x < 18.98 \\ 0 & \text{If } x < 18.63 \end{cases}$$

$$\mu_x(\text{Hold}) = \begin{cases} 0 & \text{If } x < 18.63 \\ \frac{x - 18.63}{0.15} & \text{If } 18.63 < x < 18.78 \\ \frac{18.98 - x}{0.2} & \text{If } 18.78 < x < 18.98 \\ 0 & \text{If } x > 18.98 \end{cases}$$

For the MT output variable:

$$\mu_x(\text{Sell}) = \begin{cases} 1 & \text{If } x < 0.29 \\ \frac{0.68 - x}{0.39} & \text{If } 0.29 < x < 0.68 \\ 0 & \text{If } x > 0.68 \end{cases}$$

For the variable and Sent<sub>2</sub>, the sentiment function is set as follows:

$$\mu_x(\text{Buy}) = \begin{cases} 1 & \text{If } x > 0.68 \\ \frac{x - 0.29}{0.39} & \text{If } 0.29 < x < 0.68 \\ 0 & \text{If } x < 0.29 \end{cases}$$

$$\mu_x(\text{Hold}) = \begin{cases} 0 & \text{If } x < 0.29 \\ \frac{x - 0.29}{0.21} & \text{If } 0.29 < x < 0.5 \\ \frac{0.68 - x}{0.18} & \text{If } 0.5 < x < 0.68 \\ 0 & \text{If } x > 0.68 \end{cases}$$

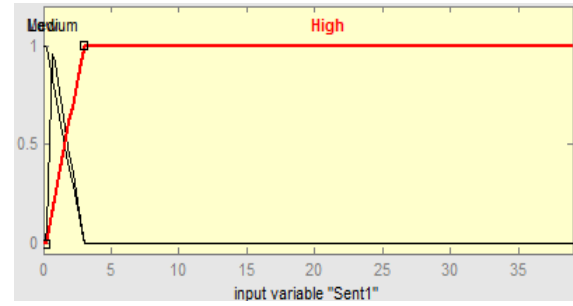


Fig. 6- Sent<sub>1</sub> input variable in the fuzzy expert system for French stock Market.

Based on the above specifications the input vs. output interface for the “Optimism”, the “Pessimism”, “Sent1” and “Sent2” input variables is presented below (Figures 4 to 7):

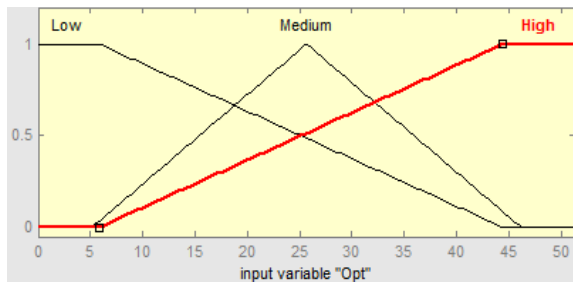


Fig. 4- Optimism input variable in the fuzzy expert system for French stock Market.

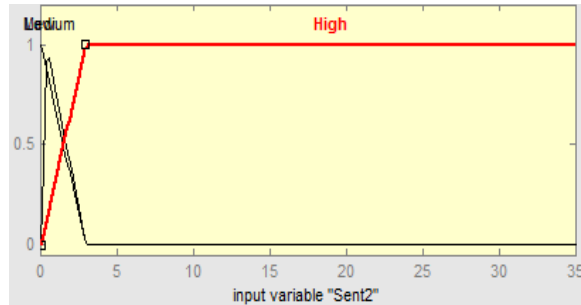


Fig. 7- Sent<sub>2</sub> input variable in the fuzzy expert system for French stock Market.

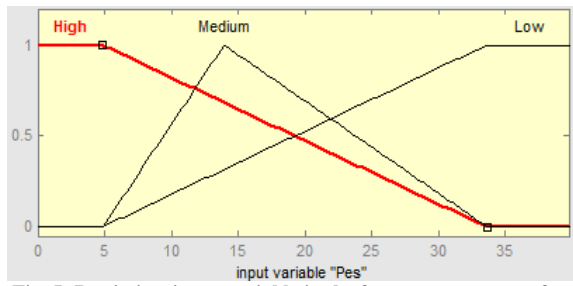


Fig. 5- Pessimism input variable in the fuzzy expert system for French stock Market.

Similarly, the output data interaction corresponding to the “Market trend” and the “Trading intensity” belief functions are presented in Figures 8 and 9:

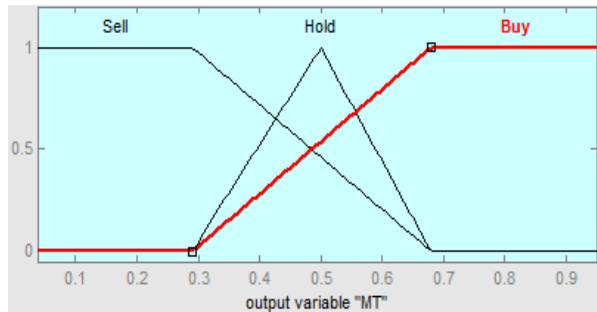


Fig. 8- Market Trend output variable in fuzzy expert system for French stock Market.

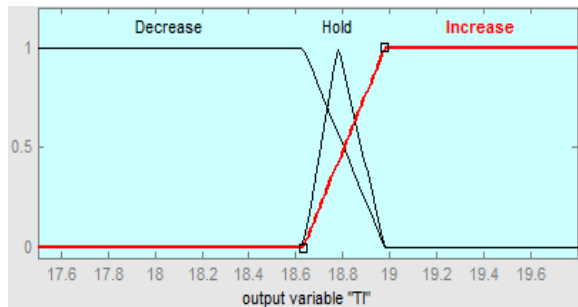


Fig. 9- Trading Intensity output variable in fuzzy expert system for French stock Market.

## ***2.2. Fuzzy rules construction***

In the proposed model with 4 inputs and 2 outputs the IF-THEN rules are formulated as shown in Figure 12. The range of each input and output variables is given in parenthesis. The range for each variable changes between the min and the max value of data. The Rules for the fuzzy logic process are analyzed in detail in Table 3. In addition, the fuzzy rule base view of the fuzzy expert system is presented in Figure 13.

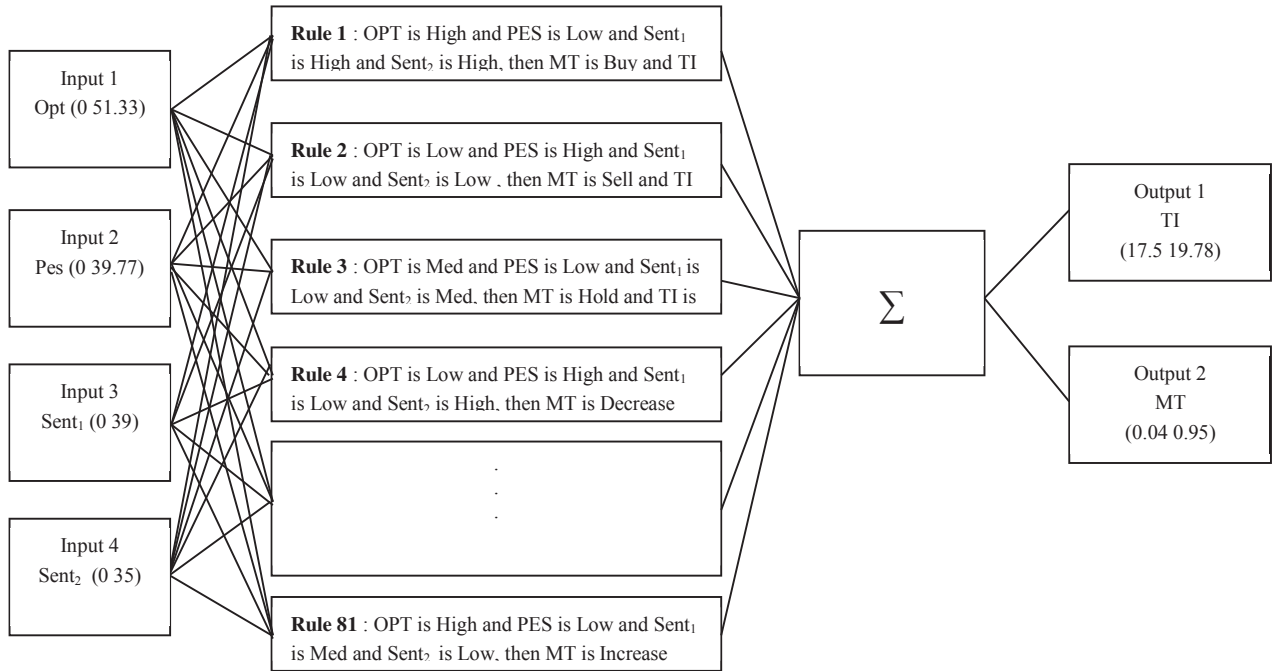


Fig. 10- Detailed structure of the fuzzy system.

Table 3- Fuzzy system Rules.

N°	If						N°	If						N°	If					
	Opt	Sent <sub>1</sub>	Sent <sub>2</sub>	Pes	TI	MT		Opt	Sent <sub>1</sub>	Sent <sub>2</sub>	Pes	TI	MT		Opt	Sent <sub>1</sub>	Sent <sub>2</sub>	Pes	TI	MT
1	High	High	High	High	Increase	Buy	28	Med	High	High	High	Increase	Buy	55	Low	High	High	High	Hold	Hold
2	High	High	High	Med	Increase	Buy	29	Med	High	High	Med	Increase	Buy	56	Low	High	High	Med	Increase	Buy
3	High	High	High	LOW	Increase	Buy	30	Med	High	High	LOW	Increase	Buy	57	Low	High	High	LOW	Increase	Buy
4	High	High	Med	High	Increase	Buy	31	Med	High	Med	High	Hold	Hold	58	Low	High	Med	High	Decrease	Sell
5	High	High	Med	Med	Increase	Buy	32	Med	High	Med	Med	Increase	Buy	59	Low	High	Med	Med	Hold	Hold
6	High	High	Med	LOW	Increase	Buy	33	Med	High	Med	LOW	Increase	Buy	60	Low	High	Med	LOW	Increase	Buy
7	High	High	Low	High	Hold	Hold	34	Med	High	Low	High	Decrease	Sell	61	Low	High	Low	High	Decrease	Sell
8	High	High	Low	Med	Increase	Buy	35	Med	High	Low	Med	Hold	Hold	62	Low	High	Low	Med	Decrease	Sell
9	High	High	Low	LOW	Increase	Buy	36	Med	High	Low	LOW	Increase	Buy	63	Low	High	Low	LOW	Hold	Hold
10	High	Med	High	High	Increase	Buy	37	Med	Med	High	High	Hold	Hold	64	Low	Med	High	High	Decrease	Sell
11	High	Med	High	Med	Increase	Buy	38	Med	Med	High	Med	Increase	Buy	65	Low	Med	High	Med	Hold	Hold
12	High	Med	High	LOW	Increase	Buy	39	Med	Med	High	LOW	Increase	Buy	66	Low	Med	High	LOW	Increase	Buy
13	High	Med	Med	High	Hold	Hold	40	Med	Med	Med	High	Decrease	Sell	67	Low	Med	Med	High	Decrease	Sell
14	High	Med	Med	Med	Increase	Buy	41	Med	Med	Med	Med	Hold	Hold	68	Low	Med	Med	Med	Decrease	Sell
15	High	Med	Med	LOW	Increase	Buy	42	Med	Med	Med	LOW	Increase	Buy	69	Low	Med	Med	LOW	Hold	Hold
16	High	Med	Low	High	Decrease	Sell	43	Med	Med	Low	High	Decrease	Sell	70	Low	Med	Low	High	Decrease	Sell
17	High	Med	Low	Med	Hold	Hold	44	Med	Med	Low	Med	Decrease	Sell	71	Low	Med	Low	Med	Decrease	Sell
18	High	Med	Low	LOW	Increase	Buy	45	Med	Med	Low	LOW	Hold	Hold	72	Low	Med	Low	LOW	Decrease	Sell
19	High	Low	High	High	Hold	Hold	46	Med	Low	High	High	Decrease	Sell	73	Low	Low	High	High	Decrease	Sell
20	High	Low	High	Med	Increase	Buy	47	Med	Low	High	Med	Hold	Hold	74	Low	Low	High	Med	Decrease	Sell
21	High	Low	High	LOW	Increase	Buy	48	Med	Low	High	LOW	Increase	Buy	75	Low	Low	High	LOW	Hold	Hold
22	High	Low	Med	High	Decrease	Sell	49	Med	Low	Med	High	Decrease	Sell	76	Low	Low	Med	High	Decrease	Sell
23	High	Low	Med	Med	Hold	Hold	50	Med	Low	Med	Med	Decrease	Sell	77	Low	Low	Med	Med	Decrease	Sell
24	High	Low	Med	LOW	Increase	Buy	51	Med	Low	Med	LOW	Hold	Hold	78	Low	Low	Med	LOW	Decrease	Sell
25	High	Low	Low	High	Decrease	Sell	52	Med	Low	Low	High	Decrease	Sell	79	Low	Low	Low	High	Decrease	Sell
26	High	Low	Low	Med	Decrease	Sell	53	Med	Low	Low	Med	Decrease	Sell	80	Low	Low	Low	Med	Decrease	Sell
27	High	Low	Low	LOW	Hold	Hold	54	Med	Low	Low	LOW	Decrease	Sell	81	Low	Low	Low	LOW	Decrease	Sell

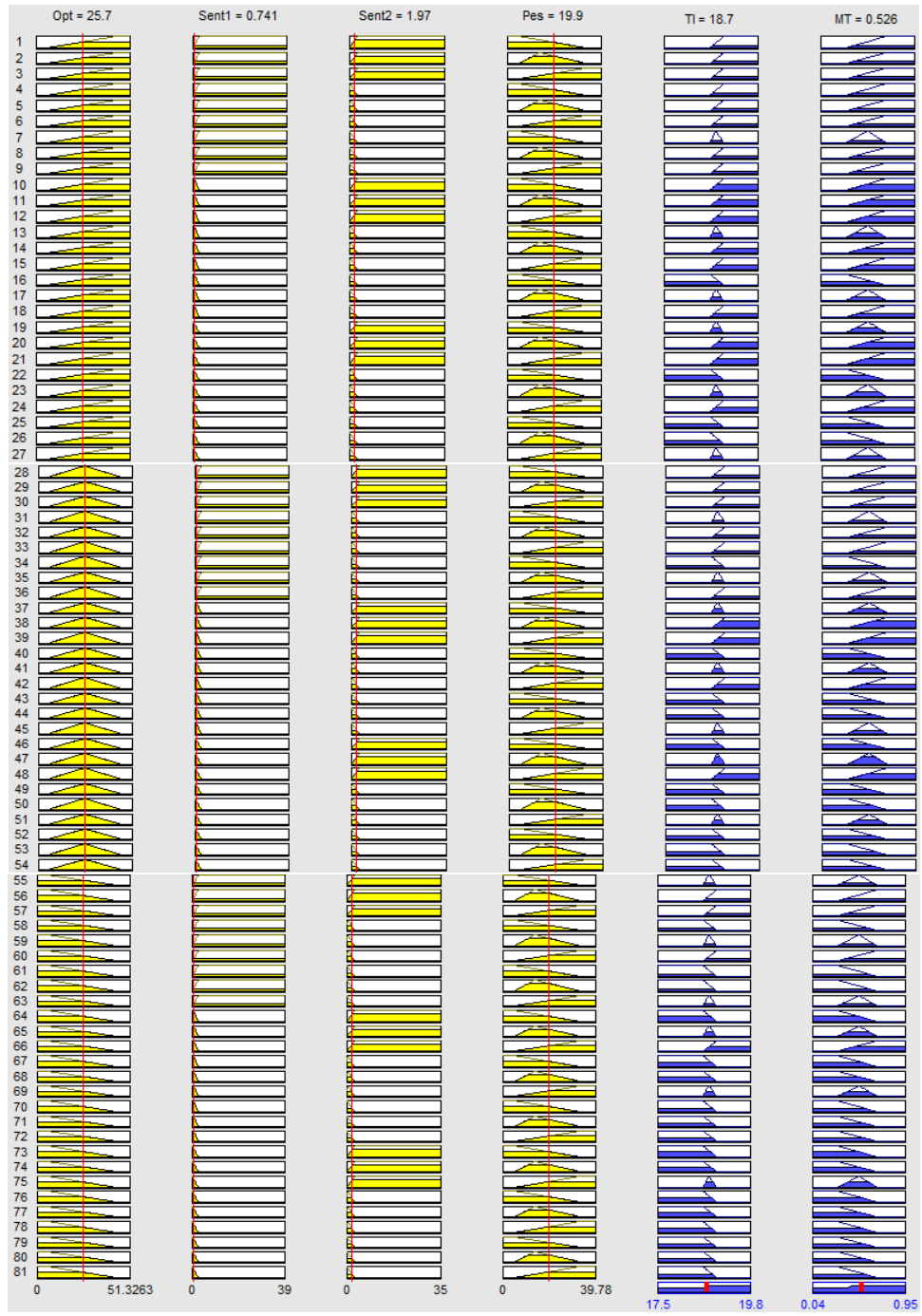


Fig. 11- Rules base view of the fuzzy expert system.

### 2.3. Results and sensitivity analysis

Figures 12 to 23 present the sensitivity analysis of the fuzzy system to trading intensity and market trend. In particular, Figures 12 and 13 show that the market trend is more sensitive than the trading intensity to the change in the range of optimism and pessimism inputs. Considering the sensitivity for the optimism and the pessimism, investors decrease slowly their trading activity even if the market trend is “Sell”, i.e., corresponding to high pessimism and low optimism. However, they increase aggressively their trading activity when the market trend becomes “Buy”, which corresponds to high optimism and low pessimism. The sensitivity to medium optimism and medium pessimism is higher for the case of the market trend output variable than for the case of trading intensity. Despite this difference in sensitivity, we see that the weight of the two inputs (optimism and pessimism) is almost identical in terms of impact on each individual output. The effect is almost symmetric.

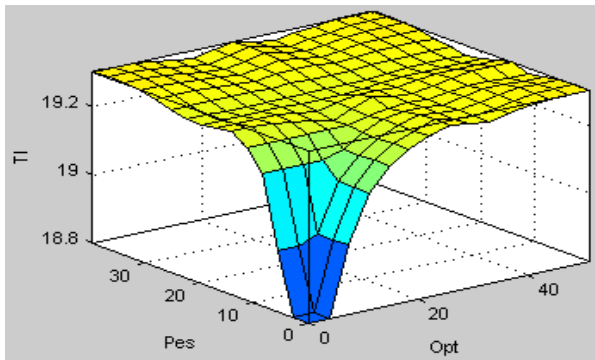


Fig. 12- Optimism-Pessimism sensitivity analysis of fuzzy system for trading intensity.

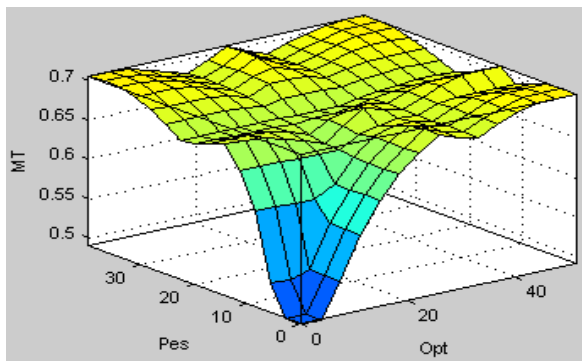


Fig. 13- Optimism-Pessimism sensitivity analysis of fuzzy system for market trend.

Figures 14 and 15 show that the sensitivity of both trading intensity and market trend to the change in range of optimism and  $Sent_1$  remains about the same with a non-significant difference in sensitivity when the input variables take the level High for  $Sent_1$  and Low of Optimism. The

sensitivity of both to the input Optimism is much higher than to the input  $Sent_1$ . We see clearly that the change in range for the optimism affects significantly the trading intensity and the market trend. Instead, only extreme value of  $Sent_1$  influence the two output variables. In fact, regardless of the change in Optimism input variable, trading intensity is “Decrease” and market trend is “Sell” when  $Sent_1$  is “Low”. However when  $Sent_1$  is “Medium” or “High” trading intensity and market trend become respectively “Increase” and “Buy”. Overall, the change in range for the Optimism input variable induces significant change in trading intensity and the market trend.

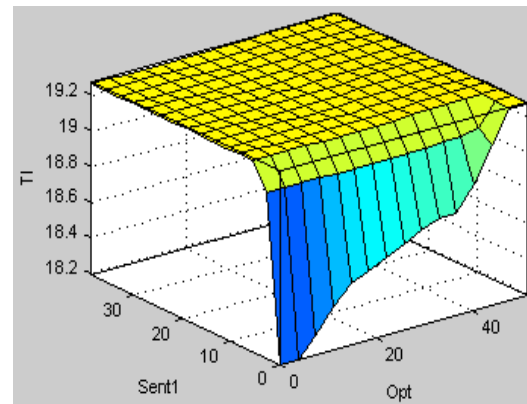


Fig. 14- Optimism -  $Sent_1$  sensitivity analysis of fuzzy system for Trading Intensity.

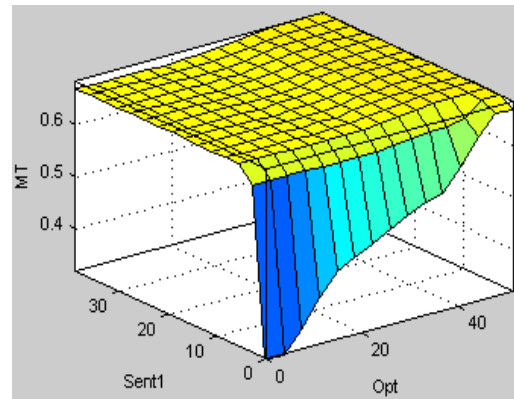


Fig. 15- Optimism -  $Sent_1$  sensitivity analysis of fuzzy system for Market Trend.

In the same way, figures 16 and 17 show similar sensitivity for both trading intensity and market trend to Optimism and  $Sent_2$  input variables. However, the sensitivity to the Optimism input variable is higher than that to  $Sent_2$  input variable. A Medium range of  $Sent_2$  has no significant effect on the change in trading intensity or the market trend. Only extreme levels (High or Low) have significant influences. However, the two output variables are significantly sensitive to the change in range of the Optimism input variable.



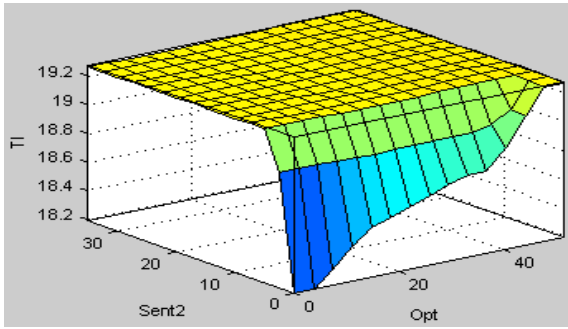


Fig. 16- Optimism - Sent<sub>2</sub> sensitivity analysis of fuzzy system for Trading Intensity.

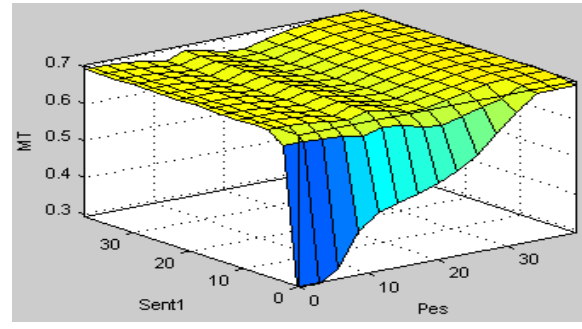


Fig. 19- Pessimism - Sent<sub>1</sub> sensitivity analysis of fuzzy system for Market Trend.

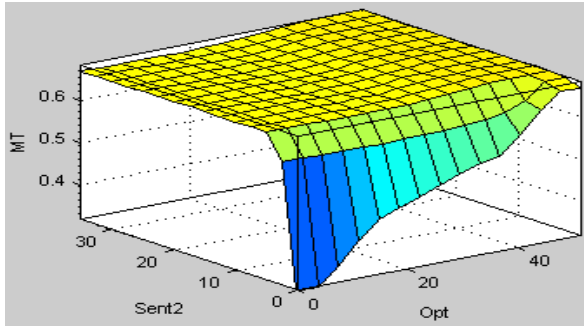


Fig. 17- Optimism - Sent<sub>2</sub> sensitivity analysis of fuzzy system for Market Trend.

Next, Figures 18 and 19 show clear differences in sensitivity for Trading Intensity and Market Trend to Pessimism and Sent<sub>1</sub> input variables. Whereas the sensitivity of the TI to the pessimism input variable is fairly smooth, the sensitivity of the MT is more observable especially when the input variable takes medium values. Moreover, the change in range for the Sent<sub>1</sub> input variable is insignificant on both TI and MT output variables once this input variable takes a medium value. The sensitivity of output variable becomes significant when the Sent<sub>1</sub> input variable is “High” or “Low”.

The sensitivity of both TI and MT to the two input variables “Sent<sub>2</sub>” and “Pessimism” is about the same to that observed for the “Sent<sub>1</sub>” and the “Pessimism” as shown in Figures 20 and 21. In fact, while TI is less sensitive to the medium pessimism, the MT is highly sensitive to this same range of change in pessimism. Medium value in “Sent<sub>2</sub>” has however insignificant impact on the two output variables.

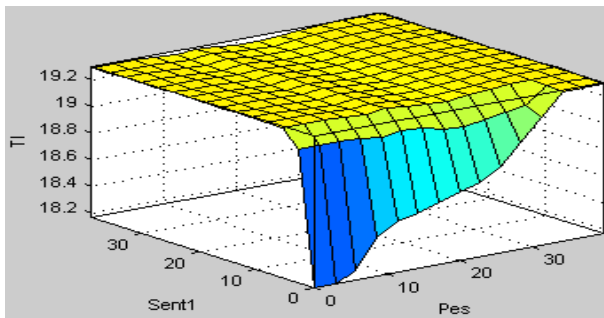


Fig. 18- Pessimism - Sent<sub>1</sub> sensitivity analysis of fuzzy system for Trading Intensity.

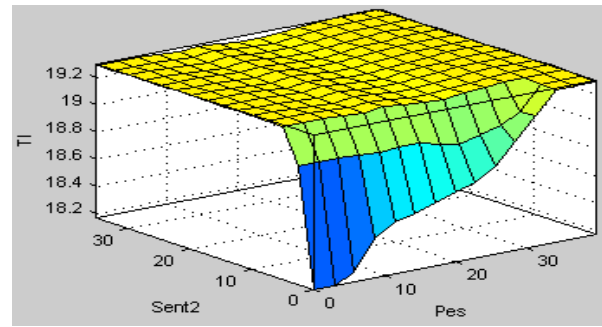


Fig. 20- Pessimism - Sent<sub>2</sub> sensitivity analysis of fuzzy system for Trading Intensity.

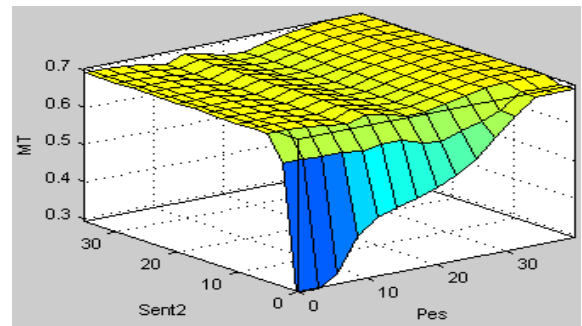


Fig. 21- Pessimism - Sent<sub>2</sub> sensitivity analysis of fuzzy system for Market Trend.

Finally, Figures 22 and 23 present that there is no significant difference in sensitivity to the change in range of the two indicators of investors’ sentiment Sent<sub>1</sub> and Sent<sub>2</sub> for both the Trading Intensity and the Market Trend. The investors tend to increase their trading and to choose the strategy Buy when both Sent<sub>1</sub> and Sent<sub>2</sub> are “High”. Once the two investor sentiment indicators are “Low” Investors tend to decrease their trading. However they prefer to Hold or choose to keep a “normal” level of trading when one single indicator of sentiment tends to be closer to the “High” level and the other indicator remains “Low”.

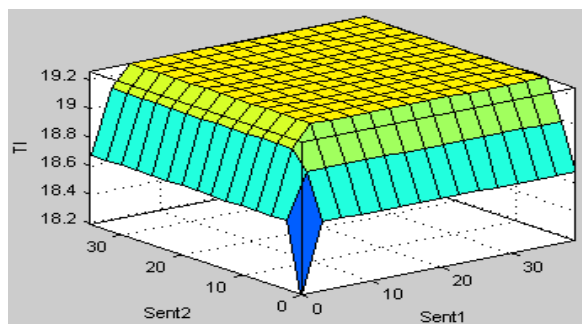


Fig. 22- Sent<sub>1</sub> - Sent<sub>2</sub> sensitivity analysis of fuzzy system for Trading Intensity.

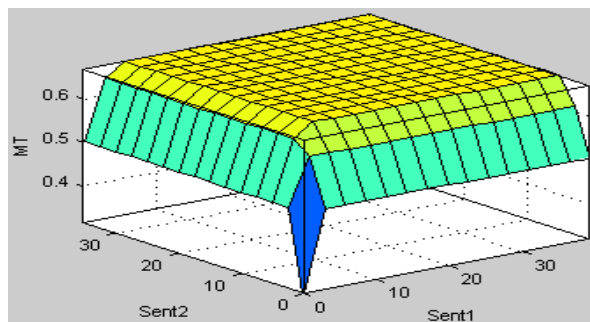


Fig. 23- Sent<sub>1</sub> - Sent<sub>2</sub> sensitivity analysis of fuzzy system for Market Trend.

These findings indicate that human psychology matters significantly when decision-making is performed in financial markets. The strategy the market agents choose (sell or buy) is significantly sensitive to the change in their anticipations and to their optimistic and pessimistic beliefs. This confirms the theoretical predictions and accords with the conclusions of Keynes (1936) that all of our decisions are taken as the result of the influence of psychological factors or “animal spirits”. Our results also follow the theoretical implications of Akerlof and Shiller (2009) who conclude that human psychology drives economies and markets and suggest to always incorporate psychological factors into macro-financial theory in order to understand “*how the economy really works*” (Kahneman, 2003).

### 3. Conclusion

This paper attempts to investigate the sensitivity of various investment strategies to the investor sentiment. We focus on French stock market because we wish to control for the level of financial sector development in this country. We revealed through an exhaustive analysis that trading intensity and market trend are both highly sensitive to investor sentiments and beliefs. Mainly, these two variables are more sensitive to a pessimistic investor sentiment than to optimistic one. This result is attributed to the fact that the optimistic sentiment can be built over the long time, but can be broken after a single shock, and hence pessimism dominates optimism. Indirect indicators of agent beliefs present more smoothed effects on these two market components. These results verify that the incorporation of psychological factors in financial modeling may lead efficiently to enhanced control of market trading behavior.

Considering the results of the fuzzy logic, investors are required to give more attention to their feelings and sentiments. The pessimistic sentiment presents a heavy impact on their decision making. Optimism can be built

over a long time but can be broken suddenly and a pessimistic sentiment rises dramatically. When making decision, investors must take into account the feeling and the sentiments of others decision makers and incorporate their perceptions as a fundamental factor having impact on the market behavior (evolution of trading and returns).

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