THE 2008 CRISIS FROM THE NEUROFINANCE PERSPECTIVE:
INVESTOR HUMOR AND MARKET SENTIMENT

Armando F. Rocha¹, Roberto Ivo da R. Lima Filho², Heitor Augustus Xavier Costa³ and Igor Ribeiro Lima⁴,

http://papers.ssrn.com/abstract=2332200

¹ RANI – Research on Natural and Artificial Intelligence
E-mail: armando@enscer.com.br
² Faculdade de Medicina – USP – Oscar Freire Institute. Address: Rua Teodoro Sampaio, 115, 1º floor – São Paulo –SP.
E-mail: roberto_ivo@hotmail.com
³ Departamento de Ciência da Computação - Universidade Federal de Lavras
E-mail: heitor@dcc.ufla.br
⁴ Departamento de Engenharia - Universidade Federal de Lavras
E-mail: igorlima@comp.ufla.br
Abstract: The world is still facing a financial crisis that started in mid 2007 and up to moment it is unsolved. Stock markets around the world reacted badly and the real time news has never played such an important role to investors as seen in previous crises. The impact of the media deepened the bear dynamics of markets around the world amplifying their volatility. Neurofinances is a new field of inquiring that has the purpose of studying decision making taking into consideration the role played by emotion. Here, we use these notions to develop a neurofinance modelling of the Brazilian stock market assuming that the investor humor is dependent on the ratio between perceived benefit and risk, as well as market sentiment. Market sentiment, in turn, is proposed to be sensitive to the kind of news delivered by the media. The model is used to study the BMFBovespa index (Ibov) evolution from January, 2003 to September, 2010 in order to test if these hypotheses hold and whether market sentiment is sensitive to an index of Good/Bad news about Ibov. Results supported present propositions.

Keywords: Finance Theory, Neurofinances, Statistic models, Decision Theory, Financial Crisis

JEL Codes: G01, G14, G17, D87
1. Introduction

The world is still facing a financial crisis that started in mid 2007 and up to moment it is unsolved. The crisis was triggered by a liquidity shortfall from the US subprime lending system that provoked financial collapse of many large important financial institutions and let others in very unstable conditions. This situation required USA Government to bailout in order to save some of these institutions from bankruptcy. Stock markets around the world reacted badly and the real time news has never played such an important role to investors as seen in previous crises. Media impact deepened the bear dynamics of markets around the world amplifying their volatility. Volatility tends to react more profoundly to negative information rather than positive one (Akerlof and Schiller, 2009). The “bad news” stemming from the crisis outweighed the “good” news, creating a vicious circle that is well-known in finance.

The US subprime crisis tested important aspects of the classical finance theory such as Theory of Market Efficiency, Modern Portfolio Theory, etc.. (Block and Hirt, 2000; Melicher and Norton, 2007), and market behavior clearly shows that investors did not behave as predicted by the academic models (CAPM, Markowitz, GARCH, etc.).

Behavioral Finance has collected a lot of evidences that investors disregard many of the assumptions of Theory of Market Efficiency (eg, Rogers, Securato and Ribeiro, 2007) such as full rationality in financial decision-making (eg, Kuhen and Knutson, 2005; Felnner and Maciejvsky; Sanfey et al, 2006; Huettel et al, 2006), or maximization of financial investment (Sanfey et al, 2006).

The influence of emotion on decision making has been used to explain deviation from optimization and that is why market sentiment is highly relevant for the understanding of the stock market. Market sentiment defines the emotional state of the financial market and it determines the movements of stock prices (Rocha, 2013). Financial market emotions are influenced by numerous factors such as market indices, expert opinion, government decisions, national and international events, contagion, etc. (e.g., Rocha and Rocha, 2011).

Neurofinances emerged as a combined effort of Neurosciences and Finances in order to better understand the dynamics of decision making in normal times as well as crisis, seeking a type of knowledge that includes neural mechanisms involved is benefit and risk analysis (Rocha and Rocha, 2011; Rocha, 2013). It is a rapidly advancing field.
providing important contributions to the understanding of economic reasoning as the result of complementary interactions between reason and emotion (e.g., Gehring and Willoughby, 2002; Huettel et al., 2006; King-Casas et al., 2005; Knutson & Knuston, 2005, Knutson et al., 2003, O’Doherty et al., 2001; Preuschoff, Bossaerts and Quartz, 2006, Sanfey et al., 2006; Tobler et al., 2007; Vorhold et al., 2007). In addition, Seymour and McClure (2008) showed people judge options and prices in relative rather than absolute terms, and anchor their future expectations on past experienced prices.

Departing from these observations, Rocha and Rocha (2011) proposed that, in trading day \( t \), the seller expects to get a price \( p^s_i(t) \) for selling stock \( S_i \) while the buyer hopes to buy the same stock at a price \( p^b_i(t) \), and they use these prices as an anchor to converge or not to a common closing price \( p^c_i(t) \) for stock trading. Both \( p^s_i(t) \) and \( p^b_i(t) \) are, in turn, expectations anchored in the closing price \( p^c_i(t-1) \) from the previous session. In addition, it was assumed that the intention to buy \( \mu^b_i(t) \) a stock \( S_i \) is dependent on the perception \( \lambda^b_i(t) \) towards the expected benefit, and the intention to sell \( \mu^s_i(t) \) the same stock is dependent on risk perception \( \chi^s_i(t) \). Both benefit perception \( \lambda^s_i(t) \) and risk estimation \( \mu^s_i(t) \) are influenced by the cost \( c^s_i(t) \) of \( S_i \). Furthermore, the conflict \( \varsigma^s_i(t) \) in deciding is assumed to be a function of \( \lambda^s_i(t) \) and \( \chi^s_i(t) \), such that it is maximum when \( \frac{\chi^s_i(t)}{\lambda^s_i(t)} \to 1 \) and minimum when \( \lambda^s_i(t) \) and / or \( \chi^s_i(t) \) tend to zero.

In this context, the humor \( h^s_i(t) \) in decision making is considered to be a linear function of \( \varsigma^s_i(t) \), that is:

\[
h^s_i(t) = \bar{h}^s_i(t) - \varsigma^s_i(t) \tag{1}
\]

where \( \bar{h}^s_i(t) \) is the a market emotional threshold at trading day \( t \). In such conditions, \( h^s_i(t) > 0 \) quantifies the optimism associated with a bull market; \( h^s_i(t) < 0 \) quantifies
the pessimism associated with a bear market. Finally, $\tilde{h}_s(t)$ is assumed to be influenced by market media news besides other factors such as government decisions, national and international events, contagion, etc.

The current work test these ideas modeling price evolution at BMFBovespa (the Brazilian bourse) in the period from January, 2003 to September, 2010. The paper is organized as follows: Sections 2, briefly describes the neurofinance decision making model proposed by Rocha and Rocha (2011). This model is used in section 4, to model BMBovespa price evolution. Section 4 discusses the correlation between the market emotional threshold $\tilde{h}_s(t)$ and media news about the Brazilian stock market. Finally, discussion and conclusions are presented on section 5.

2. Making decisions

Decision making aims to choose the course of action that best satisfy a given goal. This goal for investors is to profit on trading. For this purpose, analysis of stock benefit and risk is fundamental in financial decision making.

2.1 Evaluating Benefits and Risks

Finance theories assume expected benefit as a projection of future earnings (Block and Hirt, 2000). From Neuroscience point of view, benefit assessment is a prior estimate of the possible reward to be obtained by implementing a given action. Benefit estimation is a function of dopaminergic circuits (eg, Rocha, and Rocha, 2011; Schultz, 2004). Benefit is an analytical variable from Finances point of view, while a subjective evaluation from Neurosciences perspective.

Risk assessment is considered a function of the probability of occurrence of harmful events. Thus risk perception has both quantitative and qualitative components (eg, Vorhold et al, 2007). The neural mechanisms estimate risks usually in circumstances where information about the probability of occurrence of the events is scarce and the opportunity for analytical analysis is virtually nonexistent. In contrast special neural circuits were developed by natural selection to harm estimation. These
circuits involve primarily serotonergic circuits, and they use information about harm and about the probability of harm occurrence if available, otherwise a subjective estimation of likelihood of harm occurrence replaces probability.

In the Neurofinances context, therefore, what is important is not the expected return $r_{s_i}(t)$ throughout time $t$ for stock $s_i$ of a certain company $C$, but the subjective evaluation (or feeling) reward $\tilde{\lambda}_{s_i}(t)$ to be provided by $r_{s_i}(t)$. Likewise, what matters is not the probability of financial loss $c_{s_i}(t)$, but the perception $\chi_{s_i}(t)$ about the intensity and the likelihood of this loss (Rocha and Rocha, 2011).

Psychology has used the paradigm of assessment ratios (ratio magnitude estimation paradigm) to study sensation $S$ triggered by stimuli of varying intensity $i$. Results have shown that (eg, Bernasconi et al, 2008):

$$\frac{f(S)}{f(i)} = k$$

(2)

Many different functions have been proposed to define $f$ and $f'$. Because of this, Rocha et al (2009) proposed financial benefit to be a subjective perception of the expected return $r_{s_i}(t)$ calculated as

$$\tilde{\lambda}_{s_i}(t) = \beta_{s_i}$$

(3)

and financial risks to be a subjective perception of a possible loss $c_{s_i}(t)$ calculated as

$$\chi_{s_i}(t) = \frac{c_{s_i}(t)^{\kappa_2}}{c_{s_i}(t)^{\kappa_2} + (\theta_{s_i} - c_{s_i}(t))^{\kappa_2}}$$

(4)

Any financial index (eg Block and Hirt, 2000) can be used to calculate $r_{s_i}(t)$ and $c_{s_i}(t)$, because what matters is how the return and cost are evaluated psychologically. Moreover, it is thought that human diversity implies that different types of investors uses different $\kappa_i$ values in equations 3 and 4 for individual estimations of $\tilde{\lambda}_{s_i}(t), \chi_{s_i}(t)$. This diversity ensures that most of time there is someone wanting to sell stock $s_i$, while some others are willing to buy the same $s_i$. What is important for the model presented...
here is the use of perceived benefit $\lambda_{s_i}(t)$ and perceived risk $\chi_{s_i}(t)$ instead of the actual values of $r_{s_i}(t)$ and $c_{s_i}(t)$ for modeling decision making.

The values of the constants ($\beta$, $\theta$, and $\{\mathcal{K}_i\}_{i=1,2}$) in equations (2) and (4) are adjusted to maintain $\lambda_{s_i}(t) > \chi_{s_i}(t)$, as necessary hypothesis to define a financial market.

### 2.2 Attractiveness (suitability) of a stock $s_i$

Surveys in behavioural finance and neurofinances (e.g., Huettel et al, 2006; Kuhren and Knutson, 2005; Felnner and Maciejvsky; Peterson, 2007; Rocha and Rocha, 2011; Sanfey et al, 2006;) have shown that the attractiveness (suitability) $\psi_{s_i}(t)$ of a stock $s_i$ depends not only on the relationship $\lambda_{s_i}(t)/\chi_{s_i}(t)$ between perceptions of its benefit $\lambda_{s_i}(t)$ and risk $\chi_{s_i}(t)$, but also on the reliability $\rho_{s_i}(t)$ towards to the market behaviour in relation to $s_i$. Therefore, it is proposed that:

$$\psi_{s_i}(t) = \frac{\rho_{s_i}(t)\lambda_{s_i}(t)}{\lambda_{s_i}(t) + \chi_{s_i}(t)}$$  \hspace{1cm} (5)

so that if the:

1. perceived benefit $\lambda_{s_i}(t)$ is much greater than the risk $\chi_{s_i}(t)$ then $\psi_{s_i}(t) \to \rho_{s_i}(t)$, otherwise
2. perception of risk $\chi_{s_i}(t)$ is much greater than the benefit $\lambda_{s_i}(t)$ then $\psi_{s_i}(t) \to 0$, and
3. reliability $\rho_{s_i}(t) \to 0$ then $\psi_{s_i}(t) \to 0$, otherwise
4. reliability $\rho_{s_i}(t) \to 1$ then $\psi_{s_i}(t) \to \frac{\rho_{s_i}(t)\lambda_{s_i}(t)}{\lambda_{s_i}(t) + \chi_{s_i}(t)}$.

The current value of $\rho_{s_i}(t)$ is set, here, in the closed interval $[0,1]$ and it is assumed to be dependent among others, on investor’s success in previous investments, personality traits, etc.
2.3 Trading conflict and cognitive effort

Neurosciences have shown that decision making depends on a large network of neurons distributed in several areas of the brain (Botvinick, Cohen and Carter 2004, Glimcher and Rustichini 2004; Ledoux, 1996; Paulus, Hozace Brown 2002; Paulus and Frank, 2006; Rocha, Massad and Pereira Jr, 2004; Sanfey et al, 2003; Walton, Devlin and Rushworth, 2004). Some of these areas are in charge of evaluating benefits and risks, while some others are involved in calculating conflict generated by these perceptions of benefit and risk that determines the cognitive effort for making a decision. All these pieces of information are used by some other sets of neurons to calculate intention (willingness) of trading.

The perception of benefit and risk creates a conflict \( \zeta_{s_i}(t) \) that scale up as perceptions \( \lambda_{s_i}(t) \) and \( \chi_{s_i}(t) \) become similar, reaching a maximum when \( \lambda_{s_i}(t) = \chi_{s_i}(t) \) and goes down if \( \lambda_{s_i}(t) \) or \( \chi_{s_i}(t) \) approach zero. Therefore, Rocha et al (2009) proposed to calculate conflict as:

\[
\zeta_{s_i}(t) = -\bar{\lambda}_{s_i}(t) \log_2 \bar{\lambda}_{s_i}(t) - \bar{\chi}_{s_i}(t) \log_2 \bar{\chi}_{s_i}(t) \tag{6}
\]

where,

\[
\bar{\lambda}_{s_i}(t) = \frac{\lambda_{s_i}(t)}{\lambda_{s_i}(t) + \chi_{s_i}(t)} \quad \text{and} \quad \bar{\chi}_{s_i}(t) = \frac{\chi_{s_i}(t)}{\lambda_{s_i}(t) + \chi_{s_i}(t)} \tag{7}
\]

The assessment of cognitive effort for decision-making involves the same areas and neural circuits that estimate conflict (Botvinick, Cohen and Carter 2004, Mantini et al, 2009; Mulert et al, 2008 and Zysset et al, 2006). Therefore, Rocha et al (2009) proposed that the facility (“easiness”) \( e_{s_i}(t) \) for decision-making to be calculated as complementat to \( \zeta_{s_i}(t) \), that is

\[
e_{s_i}(t) = 1 - \zeta_{s_i}(t) \tag{8}
\]
2.4 Intention of trading

Intention to act is a complex psychological construct that requires estimating expected benefit and risk of acting in order to determine suitability to be calculated (e.g., Glimcher, 2004). The attractiveness of buying a given stock $s_i$ is determined by how much benefit (earning) is expected within a period of time, while the attractiveness of selling a given stock $s_i$ is determined by how much risk (loss) is expected within a defined future. The cognitive effort necessary to make a decision is also very influential upon the intention of acting or not. Low conflict makes decision easy and clear cut, on the contrary high conflict makes decision hard and favours procrastination (Rocha and Rocha, 2011)

In this context, the intention (or willingness) $\mu^b_s(t)$ to buy and the intention (or willingness) to sell $\mu^s_s(t)$ are calculated as follows:

$$\mu^b_s(t) = \lambda_s(t)e_s(t)\psi_s(t), \mu^s_s(t) = \xi_s(t)e_s(t)/(1+\psi_s(t))$$

The intention to buy $\mu^b_s(t)$ the stock $s_i$ increases with its expected benefit and attractiveness, while the intention to sell $\mu^s_s(t)$ to sell $s_i$ increases with its calculated risk and decreases with $\psi_s(t)$. Both $\mu^b_s(t)$ and $\mu^s_s(t)$ reach their maximum when the easiness of decision making approaches 1.

2.5 Pricing assets

Investor humor, according to equation 1, is dependent on the conflict $\xi_s(t)$ generated by the estimated values of $\lambda_s(t)$ and $\chi_s(t)$ for the stock $s_i$. If $h_s(t) > 0$, the sensation experienced by the investor is joy ($h_s(t) > 0$) or euphoria and ($h_s(t) >> 0$), while if $h_s(t) < 0$, the sensation experienced by investors will be anxiety ($h_s(t) < 0$) or even panic ($h_s(t) << 0$). In addition, it is proposed, here, that the price movement...
\( p_s(t) \) of \( s \) should be dependent on the intentions of buying (\( \mu^b_s(t) \)) and selling (\( \mu^i_s(t) \)).

Within this context, a buying market is defined if the intention to buy is greater than the intention to sell, i.e. \( \mu^b_s(t) > \mu^i_s(t) \). On the contrary, a selling market is defined if the intention to sell greater than the desire to buy, i.e. \( \mu^i_s(t) > \mu^b_s(t) \). The price \( p_s(t) \) of \( s \) increases in a buying market and it decreases in a selling market.

Because of this, it is proposed here, that market sentiment \( m_s(t) \) about \( s \) is modulated by the investor humor \( h_s(t) \) and depends on intentions of buying and selling \( s \). Recalling that \( h_s(t) = \hat{h}_s(t) - \xi_s(t) \), then

\[
\text{if } \xi_s(t) > \hat{h}_s(t) \text{ then } m_s(t) = \frac{\dot{\mu}_s(t)}{\mu'_s(t)} \hat{h}_s(t) \\
\text{otherwise } m_s(t) = \frac{\mu'_s(t)}{\dot{\mu}_s(t)} h_s(t) \quad (10)
\]

In this line of reasoning, the price \( p_s(t) \) of a stock \( s \) is be calculated as

\[
p_s(t) = p_s(t-1)(1+m_s(t)) \quad (11)
\]

i.e., the price \( p_s(t) \) in the trading day \( t \) is a function of price at trading \( t-1 \) and the market sentiment \( m_s(t) \).
3 Trading at BMFBovespa

Here, the evolution of the Ibovespa index, namely \textit{Ibov} and denoted here \( p_{Ibov}(t) \), on the trading floor of BMFBovespa from January 2003 to September 2010 in a monthly basis was obtained at http://www.bmfbovespa.com.br/indices (Figure 1A), is simulated using the financial decision model described in section 2.

![Figure 1A](image)

Figure 1A shows simulated values \( p_{Ibov}(t) \) for \textit{Ibov} anchored in its first closing value on January, 3, 2003 and market sentiment assumed constant and having a value of...
\( h_{s_i}(t) = 0.48 \) for the entire studied period. The difference between \( p_{s_i}(t) \) and \( p_{Ibov}(t) \) is shown in Figure 1B. The simulated investor humor \( h_{s_i}(t) \) varied in a nonlinear fashion as shown in Figure 1C.

Market sentiment \( h_{s_i}(t) \) imposed a nonlinear variation over \( p_{s_i}(t) \). Simulation shows that \( p_{s_i}(t) \) accompanies \( p_{Ibov}(t) \) during 2003, but from 2004 onwards the growth of the \textbf{Ibov} is lower than that estimated by the model. This difference remained stable during the years of 2004 and 2005 and started closing up this wedge from October 2007 on, reaching a negative value in May 2008. This suggested a mean-reverted dynamics of the prices as stipulated by the theory of financial time series. However, from May 2008 onwards, the value of \( h_{s_i}(t) \) reflected the change on market sentiment due to the sub-prime crisis. This shift in market sentiment marked the start of the 2008 crisis, when then the difference between \( p_{s_i}(t) \) and \( p_{Ibov}(t) \) increased again, reaching its peak in October 2008 and begun to decline again to reach its minimum in September 2010.

Figure 2 shows the \textbf{Ibov} simulation when the values of \( h_{s_i}(t) \) were ad hoc adjusted as shown in Figure 2B in order to reduce the difference between \( p_{s_i}(t) \) and \( p_{Ibov}(t) \). This procedure resulted in a near perfect fit \( p_{s_i}(t) \) to \( p_{Ibov}(t) \) because it modified \( h_{s_i}(t) \) behavior (Figure 2C). Despite of showing a logarithmic decrease over the years (\( h_{s_i}(t) = -0.0349 \ln(t) + 0.1469, R^2 = 0.9591 \)), \( h_{s_i}(t) \) remained positive for most of the period and shows two time intervals, in which it was predominantly negative. The first is the period between May and September 2008, and the second begun on August 2010. It is interesting to note here that the calculated average for \( h_{s_i}(t) \) imposed here to fit the curves of \( p_{s_i}(t) \) and \( p_{Ibov}(t) \) is equal to 0.46, a value used to set \( p_{s_i}(t) \) course in Figure 1. This new simulation confirms that the change in market sentiment characterized the crisis from May to October 2008.
Figure 2 - Ibov evolution \( P_{ibov}(t) \) from January 2003 to September 2010 and the simulated index \( P_s(t) \) calculated adjusting the emotional threshold of the investor \( \tilde{h}_s(t) \) as shown in B. Humor \( \tilde{h}_s(t) \) has varied as shown in C.

4 The impact of news upon \( \tilde{h}_s(t) \)

The previous simulation shed some light about the dynamics of investor humor and its influence on share prices. Here, it is proposed that the ad hoc \( \tilde{h}_s(t) \) adjustments (Figure 2 B) required to a better fit of \( P_{ibov}(t) \) by \( P_s(t) \) may be correlated with the influence of stock market media news upon the investor humor. For such a purpose, media news about BMFBovespa were collected from Brazilian newspapers since 2007, when the sub-prime crisis started hitting the US economy and spread out to the world.
The news were classified into bad (B), normal (N) and good news (R). This classification was made by two of the authors that are also investors. As an example, news of positive GDP’s (Gross Domestic Product) result was classified as good news (R), whilst news of negative GDP’s, which might signal a recession, was classified as bad ones (B).

Figure 3 - Good and Bad news Distribution: In the first chart has a clear normal distribution, where K=3 and S=0, whilst in the second one Bad news tends to show a Chi-square distribution with K=7 and S=1.5.

Jarque Bera test is widely used for testing whether a variable has a normal distribution or not, based on the sample kurtosis and skewness. This test showed that bad news (B) have a near chi-squared distribution (Figure 3) because of a right-handed skewness and high value of kurtosis (mesokurtic shape), suggesting a stronger impact.
on asset prices compared to good news (G), which has a normal distribution (with mean near zero skewness – they are symmetrical- and kurtosis equals to absolute three).

The ratio between B and G (\(i(\frac{B}{G})\)) news was calculated and compared to the investor humor as calculated by equation 1. Figure 4A shows the evolution of \(i(\frac{B}{G})\) and \(h_s(t)\) from January, 2007 to September, 2010.

The variables humor, \(lag_1(humor)\) and \(i(\frac{B}{G})\) were regressed as shown in table 1 and Figure 4B. The results turned out to be statistically robust: good R-squared as of 52% and no sign of (see also Predict vs Observed graph in Figure 4B). Moreover, the magnitude of the impact of news was 0.587 corroborating its important influence upon market sentiment. The variable \(lag_1\) (humor) contributes 0.37 to the investor humor and shows that the effect of news does not dissipate instantaneously. It remains hovering within the financial transactions.

<table>
<thead>
<tr>
<th>Table 1 – Regression Analysis 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression Summary for Dependent Variable: Humor</td>
</tr>
<tr>
<td>R = .72</td>
</tr>
<tr>
<td>F(2,41) = 22.23</td>
</tr>
<tr>
<td>St. Err.</td>
</tr>
<tr>
<td>Intercept</td>
</tr>
<tr>
<td>(i(\frac{B}{G}))</td>
</tr>
<tr>
<td>(lag_1) (Humor)</td>
</tr>
</tbody>
</table>

The results shown in Table 1 indicate that the ad hoc simulation of humor threshold in Figure 2 may be replaced by calculating \(\tilde{h}_s(t)\) from the \(i(\frac{B}{G})\) according to the equation shown in table 1. This hypothesis was tested by simulating the Ibov with \(\tilde{h}_s(t)\) calculated according to this procedure. The results of this simulation shown in Figure 5A and the adjustment of \(p_s(t)\) to \(p_{Ibov}(t)\) seems to confirmed the proposal.
Figure 4 – Correlation between the Good/Bad news ratio \((i\left(\frac{B}{G}\right))\) and humor \(h_n(t)\) during the period January, 2007 to September, 2007.
However, $p_s(t)$ still deviates from $p_{Ibov}(t)$ at the beginning of the 2008 crisis. So, it was also hypothesized that there exists a time lag for media crisis beginning recognition that generated higher (or smaller) good (bad) news from April to September of 2008. In the same line of reasoning it may be assumed that there were other news time lags during the beginning of the economic crisis recovering from November, 2008 on. Based on these assumptions the dummy variable shown in Figure 5C was introduced in the simulation. This resulted in a better adjustment of $p_s(t)$ to $p_{Ibov}(t)$ as shown in Figure 5B.
All these results confirmed the hypothesis that market sentiment $\tilde{h}_s(t)$ in equation 1 may be at least partially derived from the ratio between good and bad media news about the stock market.

5 Discussion

The predominant economic thinking assumes that a rational economic agent has emotion as enemy. In this line of approach, the Theory of Market Efficiency (Block and Hirt, 2000; Melichar and Norton, 2007) proposes that stock price contains all the information that investors need for rational decision-making because it performs a random path that always leads to its market value. Investor needs only this information to make decisions, because sentiments shall not interfere on financial reasoning. However, this theory has been criticized and several studies (e.g., Kim and Shamsuddin, 2008; Lim, Brooks and Km, 2008; Pasquariello, 2008) have shown that it is not applicable in times of bubbles and financial crises. The anchored price theory (see e.g., Seymour and McClure, 2008) is one of the strongest evidence that the classical theory does not adequately describe the behaviour of the investor.

Here, a neurofinance model for decision making was successfully used to study the evolution of the Ibov between January 2003 and September 2010, which was characterized by a financial bubble that has evolved from the crisis triggered by a market fall of confidence associated the U.S. housing crisis. In this model, the investor uses both their perceptions of benefit $\lambda_s(t)$ and of risk $\chi_s(t)$ to predict $p_s(t)$ the index evolution $p_{Ibov}(t)$. Important to the model are the concepts of investor humor $h_s(t)$ and market sentiment $m_s(t)$. The investor humor $h_s(t)$ is calculated from the resulting conflict $\varsigma_s(t)$ associated with assessments of $\lambda_s(t)$ and $\chi_s(t)$, and market sentiment $m_s(t)$ depends upon the intentions of buying $\mu^b_s(t)$ and selling $\mu^s_s(t)$ intentions and is modulated by $\varsigma_s(t)$.

Perceived benefit $\lambda_s(t)$ is dependent on the expected return $r_s(t)$ according to the values set for the constant $\beta$ and $\kappa_1$ in equation 3. Risk perception $\chi_s(t)$ is estimated based on the evaluation of expected cost $c_s(t)$ according to values set for the
constant $\theta$ and $\kappa_2$ in equation 4. Here, the values of these constants were adjusted ad hoc to maintain $\lambda_s(t) > \chi_s(t)$, a condition considered necessary for the existence of the stock market.

Changes in the investor humor $h_s(t)$ is the main factor for the success of the model to describe the evolution of Ibov during a period of seven years, in which the market experienced a major crisis in 2008 characterized by a period of nervousness created by the economic instability of many countries within the euro area. It is the dependence on the conflict generated by perceptions of risk and benefit that sets the general pattern of market evolution as shown in Figures 1. However, it is the dependence of $\tilde{h}_s(t)$ on local and global macroeconomic conditions that finely tune the market sentiment and dictates the evolution the simulated values $p_s(t)$ of Ibov.

Local and global macroeconomics influences are exerted over $\tilde{h}_s(t)$ and this influence is mostly exercised by means of media news, as the present results clearly demonstrated (Figures 4 and 5). In addition, these news effects over $\tilde{h}_s(t)$ are complex, because market news are also dependent on stock price evolution. Besides, the effects of the collective humor over the market are long lasting as disclosed by its dependence on lagged humor variable.

The stock price dependence on global ($\tilde{h}_s(t)$) and local ($h_s(t)$) humor as seen here, is not, however, shaped by the classical theory in finance. However, it is not any claim that the present model provides a better understanding of the behaviour of the stock market that is fundamental, but rather the fact that it can be tested empirically as done here. This kind of approach provides new interpretations about systematic and unsystematic global systemic risks (Rocha, 2013).

BIBLIOGRAPHY


