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The Adaptive Nature of Investors Risky-Preferences

Marco Antonio Souza Cauduro*

São Paulo School of Business Administration, Fundação Getúlio Vargas, Brazil (EAESP/FGV)

Abstract

The work developed on this paper aims to exploit the adaptive nature that investors perceive risk and return, emphasizing the effects that context has on decision-preferences. Based on the concepts developed on the Adaptive Market Hypothesis and The Context Theory, the empirical analysis dissecting stock returns of Brazilian companies identified that investors adjusts and adapts its risk/reward expectations based on the broad market context. The methodology used in this paper measure and ranks the Brazilian listed securities by their respective F-Score, a fundamental measurement developed by Piotroski. The findings of this paper indicate that undervalued firms consistently and significantly outperforms overvalued firms, incurring in significantly lower risk.

Keywords: Efficient markets; Risk; Return; Adaptive markets; F-score

Introduction

The objective of this paper is to bring up the discussion about the dynamic adaptive nature that investors demand risky assets, emphasizing the effects that context or structure of the markets has on decision-preferences. The rationality assumptions formulated by the Efficient Market Hypothesis seems outdated and incomplete, especially with the event of 2008 financial crisis [1]. The established rationality concept implied by the definition of *Homo Economicus* seems inadequate, and other research fields such as social psychology and neuroscience have shown how fragile our brains can be once the context or the environment changes.

This paper will explore fundamental concepts of the Adaptive Market Hypothesis [2] and Behavioral Economics theories such as the Prospect Theory [3] and Salience Theory [4], in order to explore how investors or individuals changes its concepts of rationality according to the context or risks perceived on the environment. The empirical work developed in this study suggests that the investors are live organisms changing their risk-preferences as long as they digest changes to the context.

Literature Review

The behavioral economics narrative has brought to our attention several puzzles suggesting that preferences depend on context, representing a potential contradiction with the rational choice.

The following examples are described in behavioral economics literature:

a. A car buyer would prefer to pay $17.500 for a car equipped with a radio to paying $17.000 for a car without a radio but would not buy a radio separately for $500 after agreeing to buy a car for $17.000 [5].

b. Imagine sunbathing with a friend on a beach in Mexico. It is hot, and your friend offers to get you a Corona from a nearby resort/store. He asks for your reservation price. Many people would pay more for a beer from a resort than for one from the store [6].

c. Faced with a choice between a good toaster for $20, and a better one for $30, people often choose the cheaper toaster. But when a marginally superior toaster is added to the choice set for $50, many consumers switch to the middle toaster, violating Independence of Irrelevant Alternatives [7].

d. Also, evidences from the real world also suggest that preferences depend on context.

e. When gasoline prices rise, a number of people switch from higher to lower grade gasoline [8].

f. Stores often charge extremely high regular prices for goods, but then almost immediately put them on sale at substantial discounts. The original prices and percentage discounts are displayed prominently for consumers. In some department stores, more than half the revenues come from sales [9].

g. Consumers opt for insurance policies with small deductibles even though the implied claim probabilities are implausibly high [10].

Attempting to exploit the adaptive nature that individuals take decisions or make choices, the Salience Theory [4] offers an interesting narrative that psychologists view salience detection as a key attentional mechanism enabling humans to focus their limited cognitive resources on a relevant subset of the available sensory data. It is an approach to decision theory in the spirit of Kahneman's System 1 where [11]:

- System 1 (association) shapes how we represent the problem. Attention is drawn to salient, unexpected features of the decision problem. Attention is allocated ex post, not ex ante.
- System 2 (calculation) computes what is presented to it. Salient features are over-weighted in calculations and decisions\Salience refers to the phenomenon that when one's attention is differentially directed to one portion of the environment, the information contained in that portion will receive disproportionate weighting in subsequent judgments [12].

***Corresponding author:** Marco Antonio Souza Cauduro, São Paulo School of Business Administration, Fundação Getúlio Vargas, Brazil (EAESP/FGV), Tel: +5511983830122; E-mail: mcauduro@hotmail.com

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This Salience approach requires a definition of what is usual or expected. In this model, individuals have rational expectations about their choices.

In the work of BGS [4] suggesting the Salience Theory, the authors developed and example showing how salience plays an important role on decisions. Imagining a hypothetical situation where you are buying wine in two different environments, at the store or at the restaurant:

- At the store: A wine H that you perceive a utility of 30 is selling at $20. The other wine L that you perceive a lower utility of 20 is selling at $10.

  qh=(30;$20) vs. **q**l=(20;$10)

- At the restaurant: A wine that you perceive a higher utility of 30 is selling at $60 and the other wine that you perceive a lower utility of 20 is selling at $ 50.

  qh=(30;$60) vs. **q**l=(20;$50)

The Restaurant adds $40 to the prices of both wines, and if the utility of purchasing wine is linear in price, then ranking of wines does not change. Wine **q**h is 100% more expensive in the store, but only 20% more expensive at the restaurant. Since wine **q**h is 50% better than wine **q**l, price difference is salient (noticeable) in the store, but quality difference is salient at the restaurant, where one may buy **q**l wine in the store and **q**h wine at the restaurant.

In another angle to explore Salience, according to Bordalo et al. [13], we can use Salience theory to the analysis of the demand for risky assets, once risky assets are lotteries evaluated in a context described by the alternative investments available in the market. An asset's salient payoff is naturally defined as one most different from the average market payoff in a certain time. The model presented by Salience Theory derives the notion that investors choice and market equilibrium are influenced by salience that in turn alters the demand for risky assets. This model developed by those authors is based on the fact that extreme payoffs receive disproportionate weight in the market valuation of assets.

The Salience Theory and Asset Prices [13] focuses on four well-known puzzles: First, salient thinking leads to a preference for assets characterized by the possibility of high, salient payoffs that are overweighed by investors. Second, the theory helps to explain the growth value puzzle: growth stocks are overpriced in the market because they have large salient upsides, while value stocks are underpriced because they have salient downsides such as bankruptcy. Third, the model delivers a preference for safe assets over risky ones because investors are focused on downside risks more than on equal-sized upside risks, leading to an undervaluation of risky assets. Fourth, the Salience Theory predicts counter-cyclical variation in aggregate stock market returns [14]. In bad times, the risky asset's downside relative to the safe asset is salient, and hence the risky asset is underpriced. Conversely, in good times its upside is salient, leading to overvaluation and low expected returns.

The Adaptive Markets Hypothesis (AMH) developed by Lo [2] suggests an explanation that the behavior of individuals or investors is a complex combination of multiple decision-making systems. The AMH embraces the notion described before that salience factors affect the individuals decisions under-risk, but more completely integrates the concept that individuals are live organisms that continuously incorporates their learning experiences to their decisions. The notion that the context interfere in the way individuals process all available information is very consistent with the idea lent from System Dynamics [15] that the structure of the system drives the behavior of individuals. The AMH reinforces the idea that the system and its feedbacks are continuously affecting our preferences, and the absence of negative feedbacks overtime can raise instability to the system, reinforcing irrational decisions originated most of times by greed and fear.

Along the debate surrounding the validity of the efficient market hypothesis [1], Lo [2] proposed an alternative hypothesis called adaptive markets hypothesis (AMH).

Under the EMH assumptions investors will compete to take advantage of any new information, eliminating any potential profit opportunities. In addition, psychologists and experimental economists have documented departures from empirical predictions about investor preferences implied by the EMH, suggesting that investors, at least sometimes, make decisions that are detrimental to their economic welfare. For example, individuals tend to exhibit typical risk-averse behavior when evaluating uncertain gains but tend to be risk seeking when evaluating losses, which can lead to poor financial decisions and profit opportunities for more sophisticated investors who, in effect, work to keep markets efficient. If market forces are not strong enough to overcome behavioral biases, inefficiencies can persist. The AMH suggests that rather than rely always on the "wisdom of crowds" – the logical extension of the idea that markets are always right – we should think about the creative tension between the wisdom of crowds and "the madness of mobs".

The AMH applies the evolutionary principles of competition, reproduction, and natural selection to social interactions in a sociobiological framework. Rather than viewing individuals as calculating optimizers of their utility, the AMH postulates that individuals are governed by bounded rationality under which they "satisfice" (i.e., seek a solution that is "good enough") because the costs of perfect optimization are prohibitive. The point at which individuals cease their optimizing behavior and satisfice is determined by trial and error using past experience as a guide.

Over time, heuristics that yield approximately optimal solutions develop through a process similar to natural selection. As the environment changes, however, such learned behavior may no longer be optimal and may appear irrational. Survival, therefore, requires innovation.

Just as natural selection dictates that behavior will be fitted to the environment in ecology with many species competing for scarce resources, so too will market behavior seem more rational in markets with many different types of traders. At the same time, the forces of natural selection are less powerful in environments characterized by few species and abundant resources.

The study of the interaction among all market participants and its environment needs to draw lessons from biology, ecology and systems theory. In a highly complex world, where the only way to comprehend it is to have a system-wide view that looks at the interconnectivity, the interdependence and feedback mechanisms between the parts and the whole.

Hypothesis

In this paper we examine the hypothesis postulated in the Adaptive Market Hypothesis (AMH) and The Salience Theory that investors change their risk-preferences based on context, and also adapt their behavior in order to adjust their optimal decisions.

The paper will exploit the argument that investors violate the Efficient Market hypothesis (EMH) concept of rationality and also break the established linear relationship of risk and return.

In order to identify the way that investors dynamically change their behavior according to the market's context, the study will dissect stock returns of the Brazilian stock market controlled by a fundamental score, similar to the methodology developed by Piotroski [16] called F-Score.

Methodology

Using an identical methodology than the one described on Piotroski and So [17], I have classified the strength of firms' recent financial performance trends utilizing the aggregate statistic FSCORE, as defined in Piotroski [16]. This aggregate statistic is based on nine financial signals designed to measure three different dimensions of firms' financial condition: profitability, change in financial leverage/liquidity, and change in operational efficiency. Each signal realization is classified as either "good" or "bad," depending on the signal's implication for future profitability and cash flows. An indicator variable for each signal is set equal to one (zero) if the signal's realization is good (bad).

The aggregate measure, FSCORE, is defined as the sum of the nine signals, and is designed to measure the overall improvement, or deterioration, in firms' financial condition. Firms with the poorest signals (FSCORE less than or equal to three) have the strongest deterioration in fundamentals and are classified as low FSCORE firms. Those firms receiving the highest score (FSCORE greater than or equal to seven) have the strongest improvement in fundamentals and are classified as high FSCORE firms, and firms with an FSCORE between four and six are classified as Mid FSCORE firms.

Also, the methodology classifies and allocates firm observations into value and glamour portfolios on the basis of each firm's book-to-market (BM) ratio. The method measure firms' book-to-market ratios as the book value of equity scaled by the market value of equity at the end of each fiscal year.

Then, the next step is to sort firm observations into book-to-market portfolios on the basis of the prior year's distribution of BM ratios. Following Fama and French [18], and then replicated by Piotroski and So [17], I have classified firm observations with book-to-market ratios below the 30th percentile, between the 30th and 70th percentile, and above the 70th percentile as 'Glamour', 'Middle', and 'Value' firms, respectively.

The Table 1, totally exerted from Piotroski and So [17], summarizes the framework applied to denote earnings expectations implied by Book-to-market (BM) and fundamentals (F-Score).

Data and Empirical Results

The data was extracted from the database of Economática system and also from Capital IQ platform. Both Economática and Capital IQ are database providers used by most of the market's participants such as professional money managers, sell side analysts, brokerage houses and other individuals. The database contains descriptive information about all publicly traded financial securities traded in the Brazilian Markets. Also, the database provides any type of price information (open, close, mean, etc.) of all public listed Brazilian equities and also Brazilian depositary receipts.

The sample exploited in this paper contemplates the closing price of all Brazilian listed securities that traded on average more than five hundred thousand Brazilian Reais per day, based on an average daily trading volume (ADTV) of the last twenty–one days. Cutting out non-traded and very illiquid securities, our sample contains daily data of 126 companies, from January/2002 until October/2013. Based on the nine fundamental signals developed by Piotroski [16], we calculated the daily F-Score of each company of our sample, then we generated monthly portfolios based on High, Middle and Low F-Scores. Very similar to the work developed by Piotroski and So [17], once ranked by F-scores, the securities were also ranked by Book-to-Market (BM) among Low, Middle and High BM firms. According to the Table 1, the monthly portfolios were clustered in 9 different portfolios, and then we selected to explore only the extreme portfolios of Low F-Score/Low-BM (Overvalued) and High F-Score/High-BM (Undervalued)

Using this framework, expectation errors should be concentrated in the contrarian portfolios (upper- left and bottom-right cells of the table), where market prices do not fully reflect the contrarian information conveyed by firms' fundamentals. The largest value/glamour return effect will exist between these incongruent value/glamour portfolios, where expectations implied by current valuation ratios are incongruent with expectations implied by FSCORE (Charts 1 and 2).

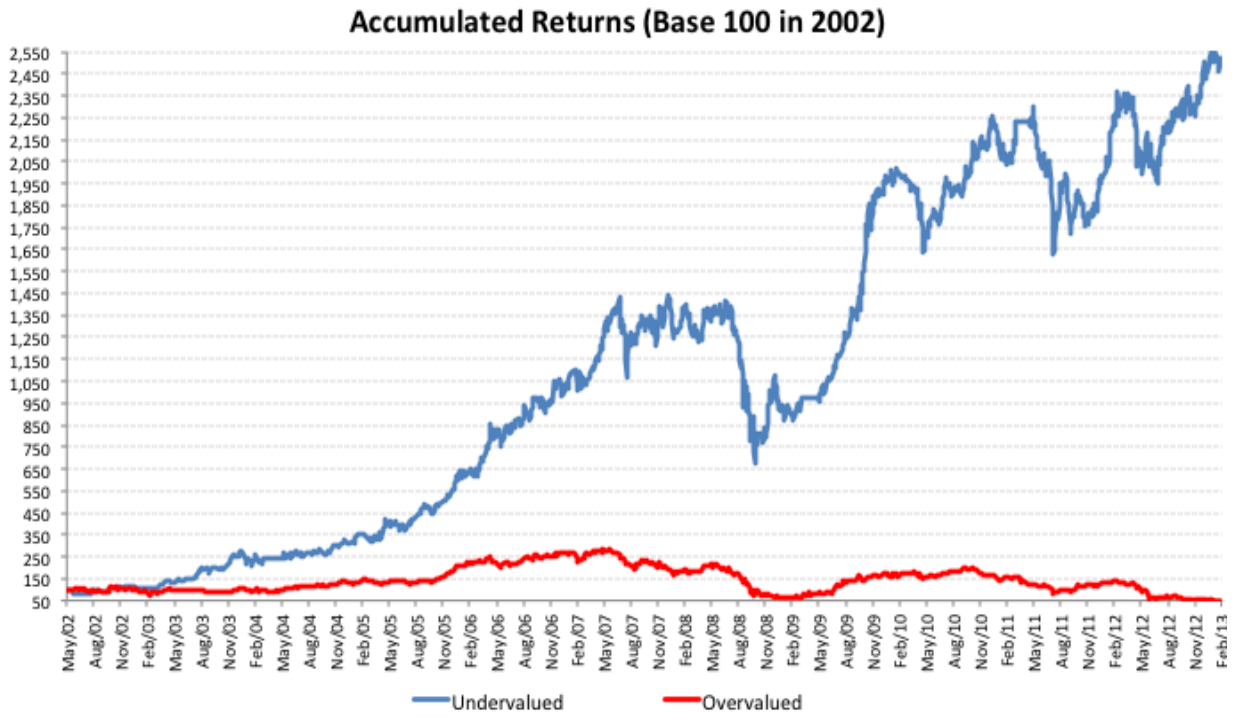
The potential returns implied on this strategy relies on the fact that earnings revisions should be strongest in these extreme portfolios, as market expectations adapt and adjust expectations according to fundamentals, and those revisions tends to be larger on value firms than glamour firms.

The Table 2 contains the descriptive statistics of both series and confirms the evidences suggested by Piotroski and So [17] but here applied to the Brazilian case, where the "undervalued" companies consistently and strongly outperform "overvalued" firms. The undervalued companies presented a daily mean return of 0,1357% compared to a mean return of 0,0046% of overvalued firms. Also, the skewness of the undervalued portfolio is positive and much higher than the overvalued portfolio, but the Kurtosis of both portfolios suggests a leptokurtic distributions. Investors' kurtosis preferences are somewhat more ambiguous and even dependent on the characteristics of the lower distributional moments. Damodaran [19] and Haas [20] suggest that the more frequent "jumps" associated with a leptokurtic distribution may produce a higher required return. A similar concept is co- kurtosis, which relates kurtosis to skewness. As noted by Guidolin

<table>
<tr><th colspan="4">Value/Glamour Portfolios</th></tr>
<tr><td></td><td>Low BM Firms "Glamour" (Strong Expectations)</td><td>Middle BM Firms</td><td>High BM Firms "Value" (Weak Expectations)</td></tr>
<tr><td rowspan="2">Low FSCORE (Weak Fundamentals)</td><td>E[E|BM]>E[E|FSCORE]</td><td rowspan="2">Potential for overvalued firms</td><td rowspan="2">E[E|BM] ≈ E[E|FSCORE]</td></tr>
<tr><td>Overvalued Firms</td></tr>
<tr><td>Middle FSCORE</td><td>Potential for overvalued firms</td><td>E[E|BM] ≈ E[E|FSCORE]</td><td>Potential for undervalued firms</td></tr>
<tr><td>High FSCORE</td><td rowspan="2">E[E|BM] ≈ E[E|FSCORE]</td><td rowspan="2">Potential for undervalued firms</td><td>E[E|BM]< E[E|FSCORE]</td></tr>
<tr><td>(Strong Fundamentals)</td><td>Undervalued firms</td></tr>
</table>

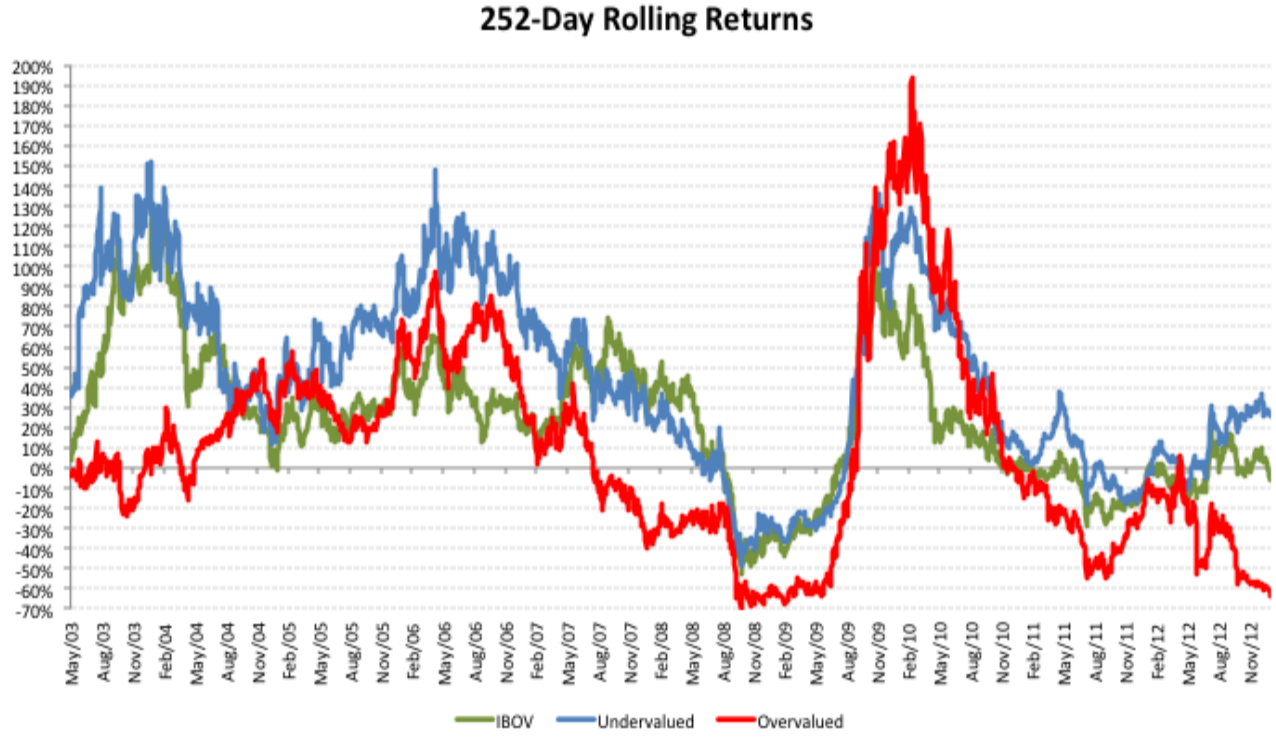
Table 1: Framework applied to denote earnings expectations implied by Book-to-market (BM) and fundamentals (F-Score).

Source: Piotroski and So (2012) Identifying Expectation Errors in Value/Glamour Strategies: A Fundamental Analysis Approach. Review of Financial Studies (RFS) [17].



Note: elaborated by the author

Chart 1: $100 invested in Jan/2002 in undervalued and overvalued firms.



Note: Elaborated by the author

Chart 2: 252-Day rolling returns of undervalued, overvalued firms and Ibovespa index.

Undervalued Firms	
Mean	0.00135701
Standard Error	0.00034652
Median	0
Mode	0
Standard Deviation	0.0180093
Sample Variance	0.00032433
Kurtosis	14.7222262
Skewness	0.22855052
Range	0.38684074
Minimum	-0.19702601
Maximum	0.18981474
Sum	3.66529289
Count	2701
Confidence Level (95.0%)	0.00067948

Table 2: Descriptive statistics of undervalued firms.

Note: Elaborated by the author.

	Undervalued	Overvalued
Mean	0.1357%	0.0046%
Variance	0.000324335	0.000589842
Observations	2701	2701
Pearson Correlation	0.44377215	
Hypothesized Mean Difference	0	
Df	2700	
t Stat	2.970733293	
P(T<=t) one-tail	0.00149855	
t Critical one-tail	1.645418181	
P(T<=t) two-tail	0.002997099	
t Critical two-tail	1.960842991	

Table 3: t-Test: Paired Two Sample for Means.

Note: Elaborated by the author.

and Timmermann [21], a high portfolio co-kurtosis value increases the chance that in a right-skewed market the portfolio return will be high, while it will be low when the market is left-skewed.

According to the t-test analysis reported on Table 3, the means are significantly different at 5% confidence level. Assuming a condition of normality on the stock returns of the series of undervalued and overvalued firms, we also reported on Table 4 the standard analysis of variance [ANOVA] tests of means confirming the difference of means. The variances of the two groups, as described in Table 5, are also significantly different between the undervalued and overvalued groups, where the undervalued series presented a much lower variance (0,032%) compared to the overvalued firms (0,059%).

The exploratory analysis conducted in this work has investigated the daily stock price returns of Brazilian securities, from 2002 to 2013, where the strong and significantly difference of mean returns between the clusters, gives a strong indicative that market participants are constantly adapting and re-adjusting risk/return expectations. Moreover, the repetitive nature of such heuristics implies that individuals do not incorporate all public available information to update their risk-preferences, an incredible delay and misperception occurs, mostly influenced by market context and investor sentiment.

A very important concept highlighted by the Adaptive Market Hypothesis [2] is the notion that risk/reward relationship does not necessarily apply across short periods. In the Brazilian case, the statistics of mean returns and variance indicates that the defined "undervalued" companies of our study delivered outstanding superior returns compared to the "overvalued" cluster, and at the same time showed a much lower volatility. The intuitive risk/return relationship did not hold most of the time-period of our study [22].

The idea developed by BGS [4] of Salience and its effects on decisions helps us to understand that a risky asset is underpriced (risk premium is positive) when its downside is salient. In contrast, the risk asset is overpriced when its upside is salient, where the risk premium is countercyclical once salience switches as market conditions change. When the fundamentals of the risky asset deteriorate and its upside approximates to the safe payoff, the downside risk becomes salient, triggering a positive risk premium. In the opposite direction, when fundamentals improve, the downside risk gets close to the safe payoff and the upside risk become salient, turning the risk premium to negative. The significantly higher mean returns of undervalued companies corroborates this concepts of salience, once companies with a higher F-score are those which the strongest improvement on fundamentals, and consequently are those companies where the upside risk become salient, triggering an increase in the stock prices (Chart 3).

The role of market movements in affecting, though salience, the risks that investors attend to can help shed new light on the observed countercyclical variation in risk premium. When fundamentals are good, investors focus on the upside of future payoffs, and overvalue the market. When fundamentals are poor, investors focus on the downside of future payoffs, and undervalue the market.

Investor sentiment and the performance of the market as whole have a direct effect on the speculative movement in market prices. In periods of high investor sentiment, the market prices imply performance expectations that deviate farther from firm's fundamentals. Exploring the data contained on Table 6, we can identify that in the Brazilian case, in "bull market" periods of high return of the Brazilian Market Index (IBOV), the difference of returns between "undervalued" and "overvalued" (Undervalued – Overvalued) stocks have decreased. In order to study the effect of the broad market context on the returns of undervalued and overvalued companies, we dissected the sample in two different periods, one high return period of the market measured by the Ibovespa index from May/02 – May/08 ("bull market"), and one down return period from Jan/10 – Oct/13 ("bear market"). We can identify on Table 6 that, during the "bull market", a strategy that buys the undervalued portfolio and sells an overvalued portfolio, generated a mean return of 0,1236% compared to a mean return of 0,1530% during the "bear market". Despite this significantly higher mean return of this strategy during bear markets, the evidence that investors are more salient to improvements on fundamentals during riskier periods it is confirmed by the strong difference of Sharpe ratios between the two defined periods. The Table 6 also presents the Sharpe ratio of 0,0264 during bull market and 0,0496 during the bear market. But the difference becomes more clear when we compare the information ratio between the two periods, where during the bear market the undervalued companies outperformed the overvalued companies hugely. Consequently, the strategy that buys the undervalued firms and sells the overvalued stocks generated a considerable excess returns.

Conclusion

We have identified that investors are constantly affected by alterations in the environment where each of them need to take decisions that involves risk.

Summary						
Groups	**Count**	**Sum**	**Average**	**Variance**		
Undervalued	2701	3.66529	0.1357%	0.00032		
Overvalued	2701	0.12443	0.0046%	0.00059		
ANOVA						
Source of Variation	**SS**	**df**	**MS**	**F**	**P-value**	**F crit**
Between Groups	0.00249	2	0.00125	3.39423	0.03361	2.99684
Within Groups	2.97441	8100	0.00037			
Total	2.9769	8102				

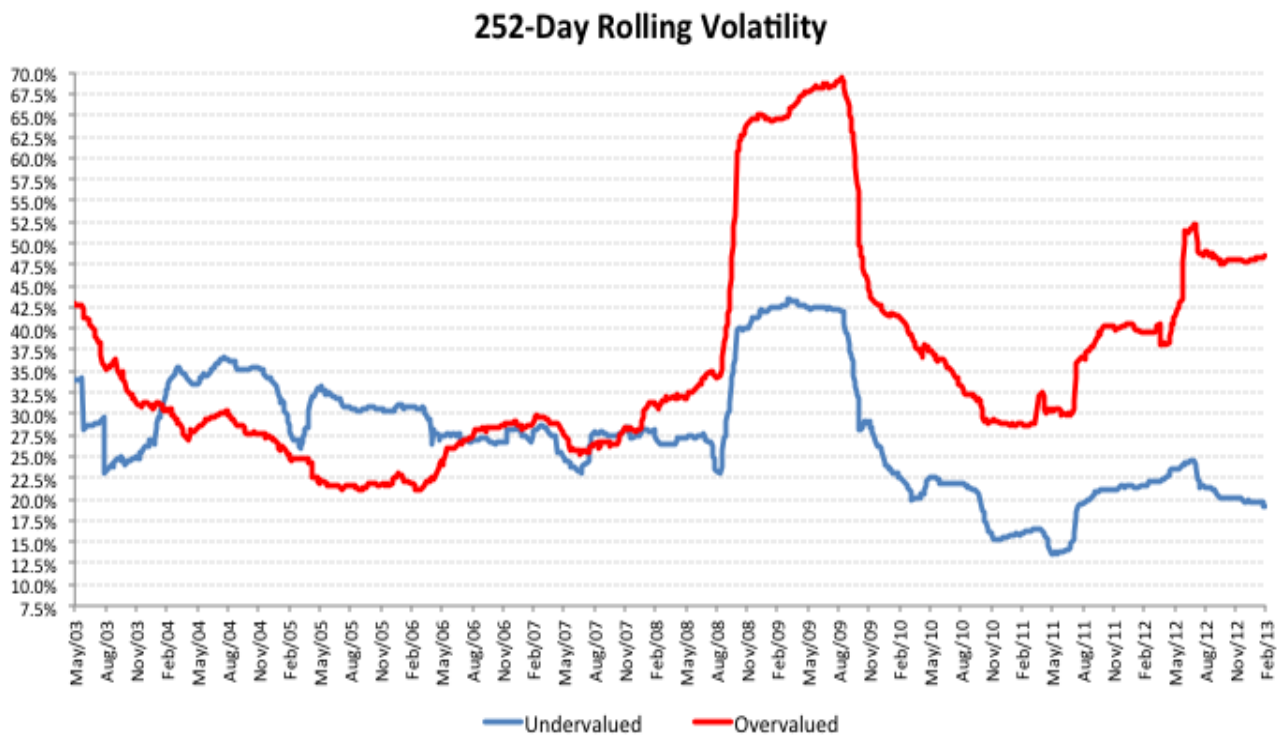
Table 4: ANOVA: Single Factor.

Note: Elaborated by the author.

	Undervalued	**Overvalued**
Mean	0.001357013	4.60669E-05
Variance	0.000324335	0.000589842
Observations	2701	2701
df	2700	2700
F	0.549867511	
P(F<=f) one-tail	0	
F Critical one-tail	0.938641562	

Table 5: F-Test Two-Sample for variances.

Note: Elaborated by the author



Note: Elaborated by the author

Chart 3: 252-Rolling volatility of undervalued and overvalued stocks.

Based on the data of Brazilian listed securities, we have identified that investors adjust their risk/return expectations according to the environment or context. In periods of favorable market conditions, the performance of undervalued companies that are improving fundamentals consistently and significantly outperform overvalued firms. Also, the relationship of risk/return, also changed on the Brazilian markets during the period studied. As described, the risk perception measured by the variance of each series of returns showed that the relationship of higher risk and higher return does not hold during the period studied.

The amount of information that is published every day and the velocity that such information moves around the globe creates an

(Undervalued-Overvalued)		Ibovespa Index	
May/02-May/08-"Bull Market"		**May/02-May/08-"Bull Market"**	
Mean	0.12%	Mean	0.13%
Standard Error	0.0005664	Standard Error	0.0004461
Median	0.001405	Median	0.0015943
Mode	0	Mode	0
Standard Deviation	2.20%	Standard Deviation	1.73%
Sample Variance	0.0004835	Sample Variance	0.0002999
Kurtosis	7.6474405	Kurtosis	0.8499583
Skewness	-0.0318387	Skewness	-0.2124995
Range	0.3606508	Range	0.1297079
Minimum	-0.1731798	Minimum	-0.066267
Maximum	0.187471	Maximum	0.0634409
Sum	1.8633607	Sum	1.9578291
Count	1507	Count	1507
(Undervalued-Overvalued)		**Ibovespa Index**	
Jan/10-Oct/13-"Bear Market"		**Jan/10-Oct/13-"Bear Market"**	
Mean	0.15%	Mean	-0.01%
Standard Error	0.0007826	Standard Error	0.0004885
Median	0.0007059	Median	0
Mode	0	Mode	0
Standard Deviation	2.18%	Standard Deviation	1.37%
Sample Variance	0.0004734	Sample Variance	0.000189
Kurtosis	13.213103	Kurtosis	2.1864491
Skewness	1.4735157	Skewness	-0.1996101
Range	0.3084307	Range	0.13185
Minimum	-0.1111601	Minimum	-0.0808514
Maximum	0.1972706	Maximum	0.0509986
Sum	1.1823936	Sum	-0.1027119
Count	773	Count	792
Sharpe ratio		**Sharpe ratio**	
May/02-May/08		Jan/10-Oct / 13	
0.0264		0.0496	
Information Ratio		**Information Ratio**	
May/02-May/08		Jan/10-Oct / 13	
-0.0029		0.0763	

Table 6: Difference of returns between “undervalued” and “overvalued” (Undervalued – Overvalued) stocks.

Note: elaborated by the author.

ecosystem where individuals are being affected in different ways by the same information. When individuals decode balance sheets or economic data, their previous experiences and the context that each of them resides, will play an important role in the way information are distilled. Moreover, any individual emotions will also change the relevance of any perturbation that new information can bring to the financial market system.

Our emotions plays an important element on our adaptive nature where unconsciously our brain has the capability to learn and incorporate on our future decision and actions previous feelings associated to potential outcomes that such action may bring to our life. Emotions become an accurate instrument because of the dopamine, the molecular source of our feelings. Scientists discovered that human brains are programmed, where they generate predictions about what will happen and then measure the difference between their expectations and the actual results.

If a cellular prediction proved false, then the dopamine neurons immediately stopped firing, where an individual experiment a negative emotion and then learn (disappointment is educational). However, if the prediction was accurate then the individual felt the pleasure of being correct, and that particular connection was reinforced. This is a crucial cognitive talent. Dopamine neurons automatically detect the subtle patterns that we would otherwise fail to notice; they assimilate all the data that we can't consciously comprehend. And then, once they come up with a set of refined predictions about how the world works, they translate these predictions into emotions.

This doesn't mean that people can coast on these cellular emotions. Dopamine neurons need to be continually trained and retrained, or else their predictive accuracy declines. Trusting one's emotions requires constant vigilance; intelligent intuition is the result of deliberate practice.

The physicist Niels Bohr once defined an expert as "a person who has made all the possible mistakes that can be made in a very narrow field." From the perspective of the brain, Bohr was absolutely right. Expertise is simply the wisdom that emerges from cellular error. Mistakes aren't things to be discouraged. On the contrary, they should be cultivated and carefully investigated.

The study of Brazilian market securities study developed on this paper can help to explain that investors are affected by emotions, sentiment and others characteristics of the system that are constantly affecting their behavior. The Salience theory brought behavioral insights that individuals became salient to what they perceive as a value maximization decision in one specific time or period. Also, most of the time, value-maximization does not mean a rational or optimal decision, especially because context and alternatives affect our risk-preferences.

The Adaptive Market Hypothesis (AMH) also reinforces the concept that the dynamics associated with the evolutionary capability that *Homo Sapiens* has to adapt and innovate according to the structure of the environment. The world has changed dramatically over the last centuries and humans were able to innovate and create solutions that promoted more harmony to our "system". The negative feedbacks received overtime and the consequent negative emotions related to several setbacks, promoted an incredible learning system on a molecular level.

In the financial world the level of transformation was also very large, especially over the last twenty years and most of the individuals (investors) are still digesting the consequences of a very interconnected and leveraged global economy. As a consequence, motivated by the emotions associated with the greed and fear sentiment, investors innovate and reinforce the instability on the system. But as long as the loops closed, individuals learn continuously from their mistakes forcing the system to restore stability.

With this tension, the Efficient Market hypothesis (EMH) and Adaptive Market Hypothesis (AMH) explains how the *Homo Economicus* interact in search for optimal decisions, that in sometimes are rational choices and in other periods are irrational. But continuously we are searching to learn, adapt and innovate.

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