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Market sophistication, an analysis before COVID-19: Valuation considering the most relevant companies of the NASDAQ-100 applying PLS-SEM algorithms

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ABSTRACT

Investors can develop behaviors that may be considered irrational from the classical economics' perspective. This research aims to generate reflective behavioral constructs, which measure the economic effects of investor decisions in the stock market. The applied algorithms' fundament is Partial Least Squares (PLS) - Structural Equation Models (SEM).

Through this approach, the analysis of dependent and independent variables that are not identically independent o randomly distributed is feasible; the advantage of this methodology is that it can apply to small samples by leveraging PLS/SEM. Complex relationships, including categorical variables, improve the models' reliability and validity by reducing the random term with an appropriate collinearity measurement.

Leverage a time series categorization for investor behavior, and path modeling is a novel procedure. Three investor categories are defined: winners, indifferent, and losers, which interact within the NASDAQ-100 stock market and the top ten enterprises in capitalization, deploying seven different phases or emotional stages ranging from financial panic to market euphoria, which reflects the investor's behavior.

Therefore, in winner enterprises, emotional and contagious effects show market bubbles, specifically on these stocks. The results also helped test the Prospect Theory's central idea: investors tend to be less excited about gains and suffers more from losses in the decision-making process. Also, to assess investor confidence and sense the dynamic market stages to find if it is undervalued or overvalued due to the investors' feedback, interactions, and sense of the market interactions.

Keywords

Investor behavior; Market efficiency; Volatility; Partial Least Squares; Risk.

Introduction and theoretical framework

There is evidence that stock returns react to market movements, and many researchers developed work around this subject. To name few of them: Capital Asset Pricing Model, CAPM (Sharpe 1964; Lintner 1965), multifactorial analysis to explain investment returns like the Arbitrage Pricing Theory APT (Ross, 1976); also, different efforts to explain market behavior performed by Baker & Wurgler (2007), Fama & French (1993, 2015), Randall, Shleifer & Vishny, (1988), and Frazzini & Pedersen (2013). The evidence leads this research to analyze returns, investments, risk, and investor behavior.

There are several ways to quantify a possible result; it ranges from different variables or the use of different statistical available methodologies, like Structural Equation Models, which are considered a second-generation methodology (Hair, Hult, Ringle & Sarstedt, 2017). This research aims to apply a novel methodology to this science field: PLS-SEM that allows complex modeling in human relationship studies, handle multicollinearity problems and lack of normality, applied to behavioral economics, adding a new proposal to categorize the market signals translated to investor emotional stages.

Market signals can also reflect investor sentiment and be collected from common market data like the NASDAQ-100 index and other indicators that measure implicit volatility and price-earnings ratio; the time effect is also an essential factor that is included within this research to define if there is a market bubble in the researched period.

The world is always changing; now, there is a new threat, COVID-19 is shaping a different standard way of living, to respond to the unexpected demand (for good or bad). Some companies attempted to modify their administrative schemes to adapt to the new requirements and reduce the economic impact of the contingency; this situation drastically changed the market procedures.

During the year 2020, the global economies have been affected by the recent COVID-19 pandemic. Unfortunately, the production capacity, the number of jobs, and the acquisition and dispositions in different fields have been adversely affected since the pandemic's emergence. From a market perspective, the pandemic's consequences leaded business sectors and companies to face significant operational, economic, and financial problems.

After this event, one of the most affected markets and at the same time widely recommended by leading investors during the pandemic is the capital market, mainly the North American stock exchange focused on the technology, electronic, biotechnological sector, which has been expressed by the NASDAQ-100 index. Current events represent a unique opportunity to analyze the market before this structural change, sensing that we are in Taleb's (2020) *extremistan*, in with rare events play a significant influence in changing the statistical properties of distributions.

Technology has been experiencing impressive growth in recent years, responding to unprecedented developments and accelerated technology research. The importance of NASDAQ-100, for both the Us economy and other world economies, derived from globalized economies' correlated effects. NASDAQ-100 is the second most important market in the United States, and this being a targeted sector before, during, and after COVID-19.

In 2019, this indicator was notoriously highlighted. It increased by 30%; after the pandemic, the index decreased by 13% (Reuters, 2020) at an unprecedented speed. It is unclear if this technology industry was naturally growing or dangerously overvalued? In a tremendously relevant market, investments in these indexes have multiple impacts on the various instruments, savings systems, and different investment alternatives when a monetary loss occurs.

Objective

This research empirically resolves if there is a trend in a wide range of periods to overvalue technology companies' stocks and analyze the contagion effect by applying second-generation econometric techniques, ideal in behavioral finance studies.

Research Methodology

A partial least squares algorithm was applied with 10,000 iterations, primarily to estimate the betas and weights; also, a bootstrap, significance calculation to transform price values of the most relevant stocks in the NASDAQ-100 index.

Paul Ekman and Daniel Cordero (2011) states that emotions are discrete, there several methodologies to classify emotions; they found evidence for universality in seven emotion categories; there is research work that employs a seven-category scheme in different fields (Li et al., 2020; Song et al., 2020; Kupekar et al., 2020). The approach applied in this research is to model market prices on a 1 to 7 Likert scale.

This procedure helped transform continuous variables, such as stock prices, into categorical variables to capture in a 1 to 7 parameter the investors' emotional stages that go from panic to euphoria.

Categorizing investor behavior is directly related to decision-making power. However, Cartwright (2016) states that Akerlof and Shiller's argument's biggest weakness is the same weakness in nearly all of the behavioral economics literature: they institutional neglect economics.

There are trading rules that naturally limits the total freedom of the operations at the market; large fund operators have to behave according to the investment guidelines when they operate; despite this, there are in the market enough large investors that have a wide range to decide freely (Kenneth et al., 2011).

Cartwright (2016) stated that "being an imperfect chooser doesn't necessarily imply an inefficient equilibrium or market failure.", this research did not consider the limited freedom effect.

There is no significant impact that prevents recording the behavior categorized under the proposed methodology; a different approach without a categorization method may require considering the institutional investor decision effect.

In a second stage in the modeling methodology, a transformation was applied to data to classify into three main categories: looser, indifferent, and winners; then in seven emotional stages as shown in Figure1:

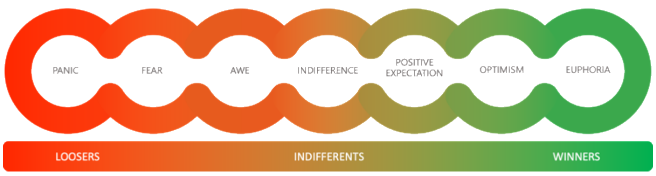

Figure 1. Emotional stages.

Source: Authors creation.

For the construction of knowledge, it is essential to define the characteristics of the constructs based on their formative or reflective character, in which the concept of reflective construct assumes specific correlation or characteristics with absolute dependence among the inputs of the construct; the formative construct takes independence from the manifest variables.

Stock prices were incorporated into reflexive constructs for each stock behavior due to the construct's nature. The defined classification goes from losers (low betas), indifferent (a beta close to 1), to winners (higher betas).

Shiller (2017) explains that narratives are:

- Human constructs
- Mixtures of fact and emotion
- Human interest
- Other details that form an impression on the human mind.

Human interests, in this case, are related to the desire to win in the market. That is why market betas capture the development of the various actions around the market and are natural trainers of the analyzed constructs.

The study proposes a second-generation econometric technique to analyze stock markets. This procedure is a hybrid methodology that includes structural equations and partial least squares and applied an exploratory analysis, finding various causal explanations, and analyzing its effects that cannot be approximated by classical methodologies, such as multivariate linear regression, which was an 18th-century technique used by Gauss before 1794 (López de Prado, 2018).

This research develops a new financial and econometric analysis methodology, which consists of transforming the time series of historical yields of the stocks, analyzed on a categorical scale that reflects human emotion, to assess the impact of human behaviors and biases, that help to understand the agents' involvement in these volatile markets.

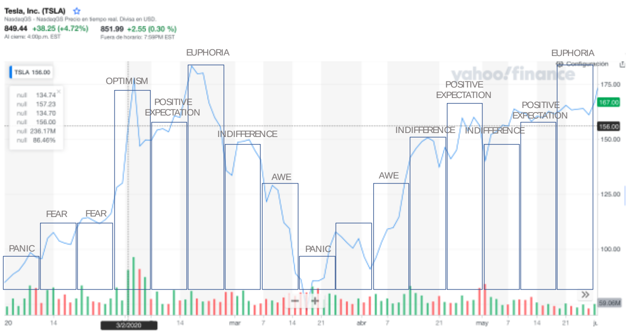

Figure 2. Example of emotional categorization of variables through the historical evolution of Tesla Inc.

Source: Authors creation based on Yahoo Finance

This categorization allows us to study behaviors such as fear, panic, optimism, euphoria and move in different emotional categories to analyze whether the market is in a bubble or undervalued.

According to the stocks market risk indicators, a recategorization procedure applied to shares that outweigh the historical behavior, which we call - winner construct - that behaves similar to the market -, the indifferent construct - and stocks that are below the market - losing construct; finding relationships between the feeling of loss or feeling of gain, and the emotional effects that are generated based on such behavior.

Constructs share similar characteristics, which overperform the market over ten years related to its correlation, such as Alphabet, Amazon, Apple, and Cisco. This construct is very similar to the historical behavior of the NASDAQ-100 index, in indifferent classified actions such as Adobe and Microsoft, finally, companies that are below the indicator that are: Amgen, Comcast, Intel, and Pepsico, given this classification, the conceptual model is made and subsequently estimated with the historical data available.

The variable applied to analyze these effects is the VIX proposed by Whaley (2017), which explains that volatility is related to higher expected return rates. When market uncertainty occurs, the best decision-making guide is the VIX, as it reflects market sentiment (Bonaparte, 2020).

The VIX measures investor sentiment. When the VIX increases, investors' fear increases and certainly implied volatility; therefore, prices should decrease. Otherwise, when the VIX (Volatility Index) falls or optimistic expectations about the market, higher yields often result.

Campbell (2014) found that asset prices appear to reflect variation in discount rates and risk premium, that valuation ratios could predict returns. These prices sometimes drift in the aftermath of events or announcements, but these drifts typically weaken over time as arbitrageurs exploit them. Kenneth et al. (2011) suggested that a valuation process is a useful tool to forecast long-term asset-class returns. There is a significant probability of success analyzing the portfolio's risk/return results over relevant long-time horizons.

There are many approaches to regressive methods and evidence of significance on shareholdings (Fleming, Ostdek, and Whaley 1995; Whaley 2000; Whaley 2009, Sarwar 2012). The CAPE (Cyclically Adjusted Price to Earnings) is an indicator exposed by Shiller and Campbell (1988), they found that the stock market can generate bubbles; Shiller (2016) comments on irrational exuberance and is as the basis of a speculative bubble.

The logic is that the price of stocks increases initially by the enthusiasm, provoked by the news, subsequently by the effect of psychological contagion, transmitted from person to person, where valuations are swept away by the envy of the success of others, who through stories are amplifying them and causing this contagious effect.

Shiller is known for his view that speculative markets are subject to long waves of irrational optimism or pessimism; this causes prices to deviate substantially from the levels if investors were rational utility-maximizers. Siegel (2016) analyzed the CAPE in a ten-year timeframe.

In this research, the same period was applied to the top ten capitalization NASDAQ-100 (Table 1), covering 54% of the index's weight due to the long term of cyclical adjusts. Facebook is not part of the analysis because it does not cover the defined ten years timeframe.

Table 1. Top Ten Nasdaq-100 companies

Name	RIC	Mcap
Amgen Inc	AMGN.O	143,756,765,909.54
Adobe Inc	ADBE.O	157,025,419,187.42
PepsiCo Inc	PEP.O	189,601,372,907.86
Comcast Corp	CMCSA.O	196,482,118,470.26
Cisco Systems Inc	CSCO.O	197,859,126,264.80
Intel Corp	INTC.O	248,689,500,000.00
Facebook Inc	FB.O	577,478,672,527.50
Amazon.com Inc	AMZN.O	884,517,114,396.60
Alphabet Inc	GOOGL.O	932,639,280,133.41
Microsoft Corp	MSFT.O	1,177,658,723,250.66
Apple Inc	AAPL.O	1,242,958,951,100.00

In PH & Rishad's research (2020), in the results they achieved, the investors are more optimistic, the market generates excessive yields, and extreme optimism leads to more speculative activities that tempt them to invest even more.

The Chicago Board Options Exchange CBOE (2003) calculate a volatility index specific for the NASDAQ-100 named "VXN" and the "VXD" for the Dow Jones DJIA. Additional research leverages the usage of VXN, and the NASDAQ-100 (Giot, 2005; Hibbert, Daigler, and Dupoyet, 2019) proposed different approaches to investigate the negative asymmetric risk-return using the VIX and VXN.

There is little research work using SEM and the VIX; Naresh, Mahalakshmi, and Thiyagarajan (2019) analyzed how changes in VIX directly influence future and spot prices of CB SEM[1] The Indian Nifty 50 Market.

The behavior (VIX) and bubbles (CAPE) determine if bubbles are present on the market before COVID-19. These indicators helped to explain and understand the importance of each of them as a reflection of the market and expose this research term: Market Sophistication, which is a mixture of feedback effects of the behavior, derived from the systematic effects of valuation and investor sentiment, that can sometimes increase the willingness to pay for the facts derived from sentiment and contagion. This phenomenon of Market Sophistication can, in return, generate biases in the heuristic behaviors or effects analyzed in behavioral finance.

Research Hypothesis

H_i: Cyclically adjusted overvaluation effects and emotional effects are statistically significant to explain NASDAQ-100 companies.

Research Model

The empirical evidence suggests there are biases about confidence in technology companies of the American stock market. This fact caused a bubble, which has recently been discounted by the same market.

Daniel Kahneman and Amos Tversky (1979) begin rethinking economic principles and precepts using wealth to trigger utility. They structured games in which the investor either wins or loses and how perspective and relativity influence human decisions. Kahneman and Tversky stated that human beings are somewhat conservative and are opposed to losing, not to the risk; the losses weigh or affect them more than profits. Valuation or perception is a function of both gains and losses and a relative perspective.

Figure 3. PLS-SEM reflects the conceptual model, the market (NASDAQ-100) is a single exogenous construct, and BEHAVIOR (VXN) and CAPE a reflective construct. Inside the circles is the R-square for each construct.

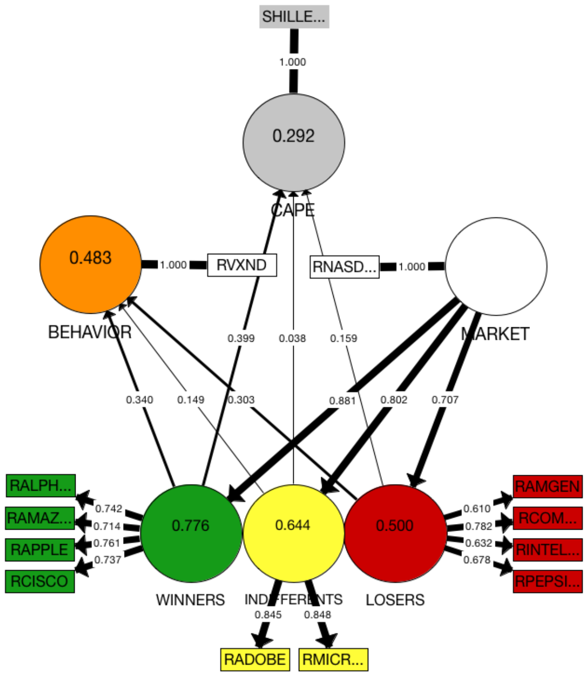

Figure 3. Path analysis, weights, and R-square of NASDAQ-100 model.

Source: SmartPLS software package developed by Ringle, C. M., Wende, S., and Becker, J.-M. 2015. "SmartPLS 3." Boenningstedt: SmartPLS GmbH, http://www.smartpls.com.

In Figure 3, there are three constructs. The first construct (green) includes the winner stocks; the second one (yellow) allocates indifferent stock symbols, and the looser stocks form the third construct (red). This analysis performed within market risk betas estimated through the OLS method, between these constructs and the NASDAQ-100 index as an indicator of systematic risk[2].

[1] Covariance-based structural equation model.

[2] Assumes that the intercept is zero.

One of PLS-SEM's main characteristics is that this method estimates coefficients that maximize the R-square or the endogenous constructs' values (Hair, Ringle, Hult, & Sarstedt, 2014). The loser stocks R-square is 50%, the indifferent construct is 64.4%, and the winner of 77.6%. Besides, an estimate of the market betas with constructs in a range of 0.707 to 0.881 in which winner stocks are more sensible or elastic than looser stocks. Another reflexive variable was formed through these constructs, Behavior-VXN and CAPE-Shiller Ratio.

Siegel (2014) explains that market prices do not always reflect fundamentals; investors can achieve superior returns by buying stocks when prices are low relative to a company's book value. There are divergences between value and price. Therefore, it is relevant to include the Shiller Cape in the market sophistication concept to evaluate market emotion and define if it has overvalued or devalued prices. Results from P H & Rishad (2020) research imply that when investors are more optimistic about the market generating excess returns, their extreme optimism leads to more speculative activities that tempt them to invest even more.

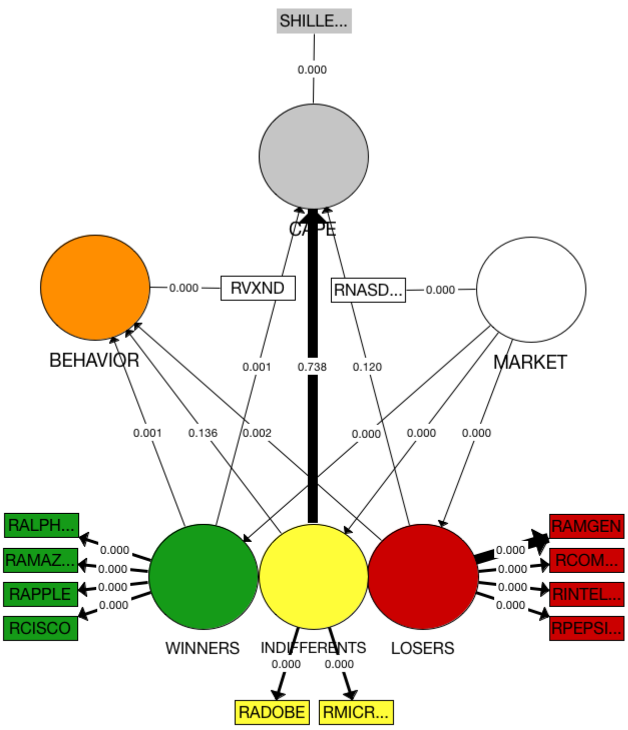

Figure 4. Bootstrapping analysis of NASDAQ-100 model (VXN).

Source: SmartPLS software package developed by, P. M., Wende, S., and Becker, J.-M. 2015. "SmartPLS 3." Boenningstedt: SmartPLS GmbH, http://www.smartpls.com.

Figure 4 shows a significant result: the stock winners, 0.34 beta, 0.001 p-values; the indifferent constructs are close to zero 0.149 betas of the 0.136 p-values, it reflects a lack of significance between this construct and the investor behavior. The losers construct records a 0.303 beta and 0.002 p-value.

Kahneman & Tversky (1979) stated that the market and its sentiment track do not reflect the Prospect Theory's downside part. Winners beta is comparable to loser's beta. This beta may indicate investor's overconfidence[3].

Pompian (2006) introduces a way to categorize biases in which the most specific category is that the cognitive part involves how people think, and emotional biases affect the way people feel. The central idea is that mental errors result from memory and information errors; dynamic errors emerge during our daily lives as an unconscious mental operation. Market efficiency is affected by the behavior factor. Wajid Ali (2019) explains two types of bias: cognitive and emotional, that exist in the personality; this affects the decision-making process (Zahera & Bansal, 2018).

Later, Pompian (2017) describes the overconfidence bias as an emotional bias with some cognitive aspects. It can also be related to another kind of biases (Blasco and Ferreruela, 2017) also interprets overconfidence between confirmation bias and cognitive dissonance. There is additional research on the overconfidence topic related to investor's decisions (Odean,1998; Barber & Odean, 2001; Statman, Thorley, & Vorkink, 2006; Markus Glaser & Weber, 2007; Grinblatt & Keloharju, 2009; Abreu & Mendes, 2012; Trepongkaruna et al., 2013; Liu & Du, 2016; Metawa et al., 2018).

Also, a critical discovery is that the R-square of VXN is 0.483. The R-square values (Hair, Hult, Ringle & Sarstedt, 2017) are the amount of explained variance of endogenous latent variables in the structural model. The higher the R-square is according to the better the construct resulted. Beginning from the Brownian behavior of stock prices (Malkiel, 2015), the R-square of a random action should be close to zero and, in its case, of the estimated Cronbach's Alpha. If the endogenous latent individual construct has an R-square above zero, this index may reflect the measure of a deterministic degree.

This research proposes a way to measure the randomness and deterministic behavior of investors' decisions. The Shiller CAPE construct registered an R-square of 29.2%. Shiller CAPE has a lack of significance in indifferent, as well as in loser constructs.

The Cronbach's Alpha is over 0.603 of overall constructs highest one is with the winners construct 0.723. Garson (2016) explains that Cronbach's Alpha can apply to experimental purposes. It can also overestimate the reliability; Cronbach's Alpha is sensible to the number of items in the scale (Hair, Ringle, Hult & Sarstedt, 2014). The composite reliability of the constructs evaluated is above 0.772. There is a detail where the AVE (Average Variance Extracted) in the loser construct is 0.460. Hai, Hult, Ringle,

[3] Defined as unwarranted faith in one's own thoughts and abilities.

and Sarstedt (2017) suggest that if this indicator is below 0.4, an alternative to solve this is to withdraw some of the analyzed companies, which is not the case.

Regarding the multicollinearity and structural collinearity, Garson (2016) suggests that in a well-fitting model, the structural VIF should not be higher than 4. In this analysis, the maximum VIF reported is 2.327 in the case of an indifferent construct, showing no multicollinearity. The f-square metric registered a minor dropping effect in the indifferent construct, compared to the 0.02 cut off (Cohen, 1988; Garson, 2016).

The Q-square of CVR (Cross-Validated Redundancy) is more significant than zero; this provides a valid prediction. Alternative constructs, cross-validated communality, Q square, expressed as 1-SSE/SSO following Cohen (1988) and Garson (2016), are in a valid range of (0.144 to 0.252).

Market Sophistication Equation

In the context of this research, the decisions implied a mixture of information and different temporalities, i.e., the investor executes valuation exercises based on historical data and impacts from other investors that generate changes on the market. This behavior leads to changes in economic performance –not always rational– resulting in cycles-valuation; as mentioned by Kantor & Hosldsworth (2014), "Valuations catch up with economic performance, or performance catches up with valuations."

Further research is required; however, a priori, there is no clear antecedent-consequent identified, but the feedback does affect the market. According to Shiller's CAPE, this cyclical behavior may justify why the exercises are not purely formative, but reflective.

The PER[4] based analysis is relevant to understand market effects and predict future behavior that may belong to specific levels; however, this method's predictive power or the volatility is not proof of market irrationality, as Kantor & Hosldsworth (2014) expressed.

The market sophistication comes from the macroeconomic environment, business fundamentals, and the volatility fueled by the performance-valuation cycle phenomenon (Figure 5). This dynamic reinforces the desirability of using Shiller's CAPE and Whaley's VIX/VXN in this research.

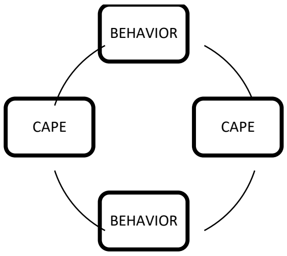

Figure 5. Market sophistication and feedback.
Source: Authors creation.

The CAPE's predictive power comes from the inference, attributed to the marginal benefit that the investor is willing to pay for units of profit of the companies; the data analyzed with this method could indicate the potential growth of the companies (Bodhanwala, 2014).

This research found evidence that the overconfidence bias is present in the NASDAQ-100 market performance and measured by the VXN. Barber & Odean (2000) stated that some irrational decisions might provoke underreactions or overreactions that stimulate effects and make inefficient markets. Overconfident investors tend to overestimate their private information's value, causing them to trade too actively, earning below-average returns. (Ali, 2019).

Winner-BEHAVIOR and winner-CAPE constructs reflect the idea of irrational exuberance. The rice of prices (the most significant betas) in the winner construct gets detonated by some market news, as it is amplified by enthusiasm (the most considerable CAPE reflexive betas). In this research, it is also relevant to propose a Market Sophistication (MSIN) Index in the specific case of NASDAQ-100; therefore, the deterministic impact on the winning stock constructs can be evaluated as follows:

$$MSIN=\frac{1}{2}\left([\beta_{VXN}][R_{VXN}{}^{2}]+[\beta_{CAPE}][R_{CAPE}{}^{2}]\right)$$

$$\frac{1}{2}\left([\beta_{VXN}][R_{VXN}{}^{2}]+[\beta_{CAPE}][R_{CAPE}{}^{2}]\right)$$

(1)

Whenever, $|\beta_{VXN}\in\mathbb{R}>0,\beta_{CAPE}\in\mathbb{R}>0;$

$|\beta_{VXN}\in\mathbb{R}>0,\beta_{CAPE}\in\mathbb{R}>0;$

Therefore, if:

$MSIN \sim 1 \Rightarrow Deterministic\ market$

$\sim 1 \Rightarrow Deterministic\ market$

$MSIN \sim 0 \Rightarrow Random\ Market$ $\sim 0 \Rightarrow Random\ Market$

The first part of the equation $[\beta_{VXN}][R_{VXN}{}^{2}]$ $[\beta_{VXN}][R_{VXN}{}^{2}]$ reflects the impact of the VXN on the winning stocks, and the

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[4] Price Earnings Ratio.

second part $[\beta_{CAPE}][R_{CAPE}{}^2][\beta_{CAPE}][R_{CAPE}{}^2]$ refers to the impact of CAPE on winning stocks.

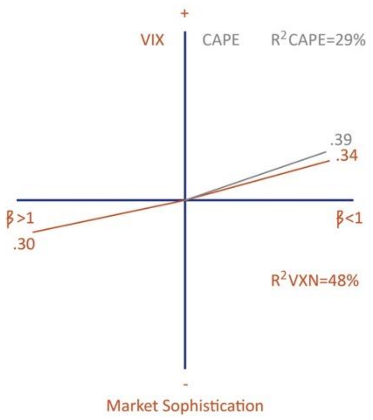

Figure 6. Prospect Theory by Kahneman, D., Tversky, A. (1979).

Source: Authors creation

The first part in figure 6 shows the impact of the VXN winner's stocks, and the second part is related to CAPE's effect on the winning stock constructs.

According to his betas, the chart reflects the initial idea of Market *Sophistication* as measured by NASDAQ-100 winning companies and losers representing the x-axis. Initially -in quadrant one- regular results are presented for the winning companies, reflecting the VIX's effect in orange and CAPE's in gray.

An inelastic curve is in looser companies; however, an elastic function is present according to the real data. It reflects overconfidence, confirmation, or cognitive dissonance in the performance of the NASDAQ-100 represented in orange in Figure 6.

The biases can be quantified, not only on the NASDAQ-100 market but also on any other market.

The behavior of the winning constructs, measured through the cyclical overvaluation adjusted effect (CAPE), reflects the idea of *irrational exuberance.*

Winning companies -the significant betas- affected by market news, amplified by collective enthusiasm, reflect a bubble that does not occur in the loser companies, as reflected in gray on Figure 6.

Using both indicators and analyzing the winning or losing nature, it was possible to identify which dimensions helped determine and explain the behavior through the R-square.

Comparing the VIX versus CAPE's R-square, the first had a higher explanatory incidence on winners and losers versus the second that only had a significance on winners.

The *Market Sophistication* was generated only in the winning construct; thus, this methodology helps evaluate the degree of assertiveness by taking the R-square as an indicator of a deterministic market instead of randomness.

The proposed methodology provides a tool to model the *Market Sophistication*.

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