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Investor Behavior and Economic Cycle:

The Impact of Human Factors on Economic Booms and Busts with a Global Perspective

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Abstract

For more than half a century, the efficient market hypothesis and the rational expectations theory had been the milestones for policy makers and regulatory benchmark in the financial industry in the US and other OECD countries. In the past decade, however, these theories were considered to have worked only in their weak forms and many believe that financial markets have been dominated by characteristics of human psychology.

In light of the severe financial recession and economic bust we just experience, this paper examines whether market participants' biases and cognitive limitations had contributed to the severity of economic cycles and how these human factors were revealed taking into account the dynamics of regulatory, technology, and market changes and the global shift in the investment community. Specifically, we search for (i) whether market participants' behavior had exacerbated the baseline dynamics of an economic cycle across time (ii) what and how each behavioral characteristic had contributed to a cycle when market rules change using time series and panel data and (iii) what policy makers and regulators could do to discourage excessive behaviors while maintain certain market autonomy that leads to more sustainable growths in an economy.

While previous findings suggest that the excesses of market volatility were attributable to human factors, illustrated by over/under-confidence, heuristics, mental framing, and other traits, this study demonstrates that market deviates more from the technical fundamentals when it renders the opportunity for more human expressions and ultimately leads to higher magnitudes and frequencies of economic booms and busts.

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1. Introduction

Since the industrial revolution in the late 18th century, the occurrence of economic cycles was the norm due to imperfect monetary policies and regulatory system and the unstable nature of a demand and supply based market economy with multiple agents in a varied time horizon. While most nations strive for a goldilocks economy with various monetary and fiscal policies in place for growth and social stabilities and sustainability, the frequencies and magnitudes of economy cycles occurred in the US and its trading partners in the recent past had generated short- and long-run costs that severely impacted lives around the globe.

During an economic expansion, assets were overvalued while consumptions went overboard and incomes were redistributed or reallocated to a small percentage of the population that further exacerbated inequality, a root cause contributing to the current crisis (Raghuram Rajan, 2005). In a recessionary economy, such as the one we are experiencing, millions had lost their homes, jobs, life savings, and are deprived of aspiring educational as well as professional experiences. The quality of lives of millions of Americans had been sabotaged and the estimated damages in dollar terms to be $8.3 trillion which includes savings and investments, pensions, home equities, and retirement assets. At the aggregate level, population in the U.S. had lost about a quarter of its net worth.

Since the Great Depression in the 1920s, all severe economic booms and busts were reflected in the performances of stocks in the capital markets as illustrated in Figure 1 below. After the WWI and before the 1929 Great Depression, stock price had a steep appreciation as a result of excesses, high leverage, and speculative investments in the stocks. The market crash came after the real estate values declined. In more recent decades, the surges of stock prices during the boom time were triggered by new or innovative development in specific industries or

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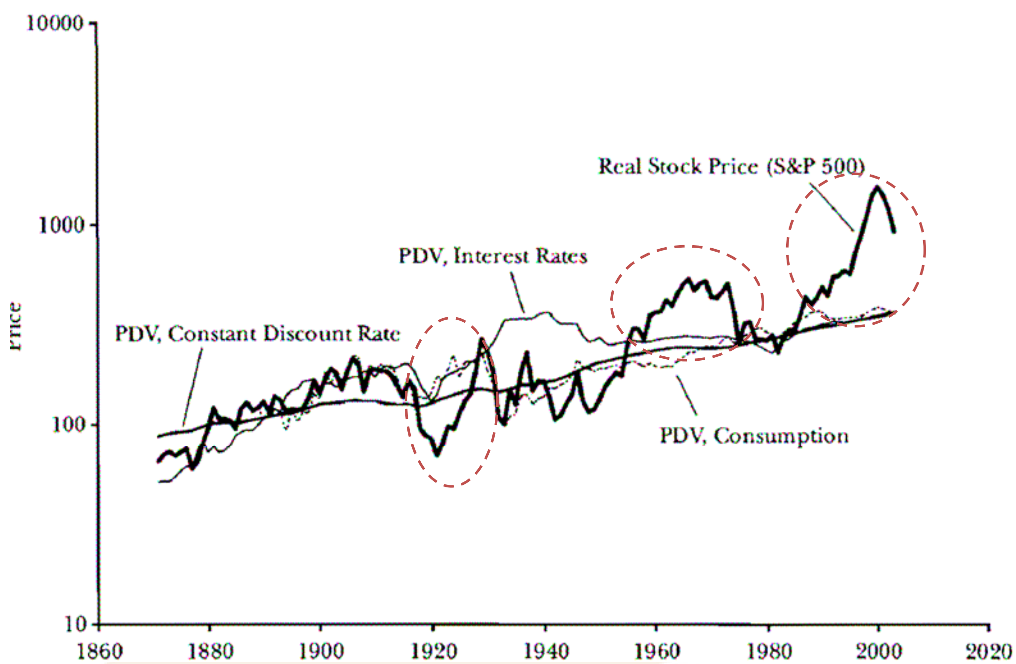
products, e.g., the dotcom bubble in the 1990s and the subprime mortgage backed securities started in the mid-1900s (see Figure 2, the Nasdaq Index with heavy technology stocks and Figure 3 shows stock prices of Bank of America Corporation and a real estate equity representing the financial industry boom and crash originated in the real estate related investing).

Figure 1



Source: Robert J. Shiller, “From Efficient Markets Theory to Behavioral Finance.” Journal of Economic Perspectives Vol. 17, No. 1, Winter 2003, pp. 83-104.

Note: The present discounted values represent the efficient markets model in various forms.

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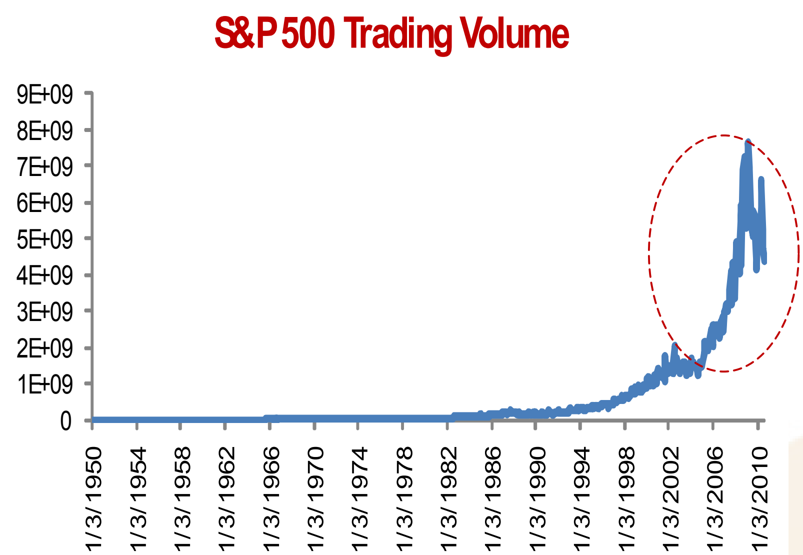
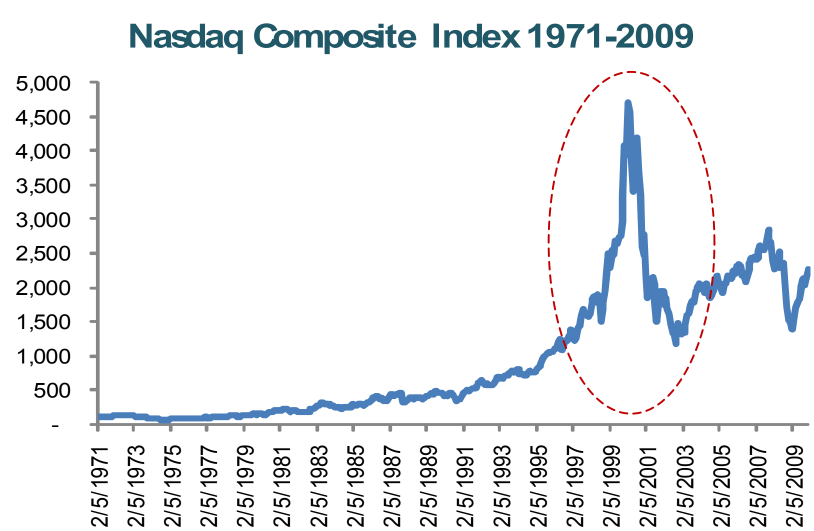
Figure 1A



Source: Yahoo! Finance

Figure 2



Source: Yahoo! Finance

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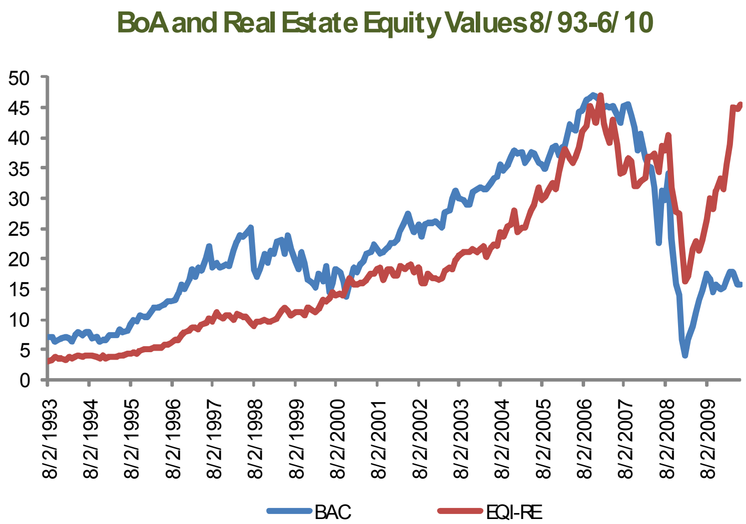
Figure 3



Source: Yahoo! Finance

While the level of volatilities and asset values surrounding economic booms and busts were beyond what the weak form of the efficient market hypothesis (EMH) is able to impose, this paper proposes that the behavioral fundamentals, the behavior of market participants attributable to human nature, emotions, and cognitive limits that lead to biases reflexive of the dynamic and complex externalities, may fill the void. In addition, given that the financial industry had accounted for 8% of the GDP (approximately 40% of all corporate profits in the US), household debt had grew to 98% of GDP in 2007 just prior to the catastrophic financial meltdown, and the magnitude of the stock prices had deviated from what the rational model prescribes, the study demonstrates that human factors may have caused the economic cycles or the aftermath shocks to be much more severe than what the ruling paradigm of modern finance expects.

Moreover, given the impact of changes in financial regulations and policies on the market structures in terms of industry expansions and product development in the past decade, this paper

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takes the opportunity to explain how these changes have not only created incoherent or conflict of beliefs in political and economic terms that short-circuited the 2008 crisis (Chang, 2005), but also exacerbated the profit driven nature of the financial industry on the one hand and debilitated investors' cognitive understanding of the market mechanisms further due to complex yet structurally unsound innovations on the other, taking into account human nature and the social and incentive structures at the corporate, industry, and political levels.

Consider the destructive effects of stock market crashes: (1) the dotcom event caused the loss of $5 trillion in the market value of companies from March 2000 to October 2002 (2) The IMF estimated that financial institutions worldwide will need to write off $1.5 trillion of their holdings of subprime mortgage backed securities (MBS) while about $750 billion in such losses had been recognized as of November 2008. These losses are expected to top $2.8 trillion from 2007-10. U.S. bank losses were forecasted to hit $1 trillion and European bank losses will reach $1.6 trillion. Our research questions are:

I. Financial markets develop over time. In the past decades, how the market has evolved in terms of changes in technology, regulation, and financial innovations? Is there a relation between these changes and changes in population disposition in the investment space in an economy and what are the purposes and consequences, in terms of costs of benefits, of these creations in short- and long-terms.

II. What are the ramifications of changes in market rules and conditions in terms of influencing population behavior - whether market participants' behavior had exacerbated the baseline dynamics of an economic cycle across time beyond the explanation of existing theories under rational expectations?

III. There are conflicts of interests between drivers of behavior in finance and those for the overall economic well-being. What and how human behavioral characteristic had contributed to a cycle when market rules and conditions change - what are the misalignment and misunderstood/unrealized consequences of these changes in the implementation process? Have these changes harmed the overall economy or had adverse consequences in the economic shifts because financial behavior differs from that of the general economic interest due to differed motivational dynamics and structures of human behavior? And what mechanisms can be applied in reconciling the differences in achieving general equilibrium?

IV. Given the fundamentals of human nature and cognitive limitations in a dynamic and complex global market that could lead to structured biases or idiosyncratic deviations from technical fundamentals at the individual/industry level that cause the market to shift, what model could reflect the combined forces more accurately given the reflexive nature of market behavior so policy makers could discourage excessive behaviors while maintain certain level of market autonomy that leads to more sustainable growths in an economy?

The significance of the paper includes (1) better prediction, explanation, and control of financial performance and allow new development in financial models with empirical findings for more efficient management of capital (2) aspiring new development of theories in finance and economics with more weights on behavioral fundamental and bridge gaps between theory and the reality (3) reconciling different objectives between finance and economics for the greater good with optimization approach (4) better policy and educational apparatus given human characteristics for better prediction and control therefore the well-being of the economy.

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In the following sections, a brief history of economic cycles will be reviewed with propositions highlighting human factors observed during these events. Specific psychological traits and symptoms from previous research results attributable to the cycles are presented. A model of multi-agents is proposed and statistical findings are discussed. Finally, regulatory and policy implications are remarked given results.

2. Human Nature, Emotions, and Responses - The Interconnectedness and Feedback Mechanisms Among Regulatory Transformation, Market Structures, and Investor Beliefs – a Physiological and Psychological Approach

While the efficient market hypothesis along with the rational expected theory had been challenged under many circumstances, this paper intends to shift the weight of the EMH in its dominance as an explanation of market performance and behavior given limitations of arbitrage[1] and the complex development of a global market thus introducing the impact of human factors as an important driving force of economic cycles. The following passages explain the interconnectedness of various forces in propositions.

Proposition 1: *The behaviors of market participants were pro-cyclical due to human nature and other cognitive biases which fed the booms and intensified busts.*

From Figure 1, we observed that almost all major economic booms and busts were led by stock surges and crashes that were beyond the present value of an economy at the time or what the EMH is able to explain. Nevertheless, recent findings in behavioral finance had attributed these shared characteristics to human nature and shortcomings, e.g., greed, fear, emotions, or biases such as herding and overconfidence that will be discussed in the following section. In the case of the Great Depression in the 1920s, the average P/E (price to earnings) ratio of S&P

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Composite stocks was 32.6 in September 1929. The rising share prices encouraged more people to invest, a symptom of heuristics (representativeness, availability, anchoring) and herding, thus fed the boom. After the economic bubble busted, the psychological effects of under-confidence dominated, which intensified the downturn that led further to declining consumption, hiring, and money supply – a great depression was created.

Proposition 2: *A specific innovation or industry development that drove the trend*

Figure 2 and Figure 4 show that technology development in the 1990s and credit expansion in the 2000s were the innovative driving forces of the booms. While the dot.com evolution as a development in technology had been beneficial to some and the subprime mortgages and other investment instruments were intended to profit a larger pool of populations in homeownership and in receiving higher investment returns, excesses, magical thinking and cognitive limitations in understanding the nature of these products due to information asymmetry and other externalities as a result of a dynamic and complex market structure with many conflicts, limits of resources, risks and pitfalls had yet again led market participants to another bubble (see Figure 5). The number of homes bought for investment jumped 50 percent during the four year period ending in 2004, according to the San Francisco research firm Loan Performance.

Proposition 3: *Regulatory transformation led to changes in market structure - the underlying conditions that caused chain of reactions - the unique features of the 2008 crisis:*

According to Pavlov's Classical Conditioning experiment and theory, learning is a formation of association between environmental stimuli and behavioral response (S-R). Applying this behavioral theory, we've learned that various forms of deregulations, such as the

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Marquette Ruling in the late 1970s and the elimination of the Glass Steagall Act in 1999, had served as conditional stimuli for massive expansion in the consumer credit market (Chang, 2008) and allow freedom for various financial innovations leading to the current crisis as a response (see Figure 6).

Figure 4

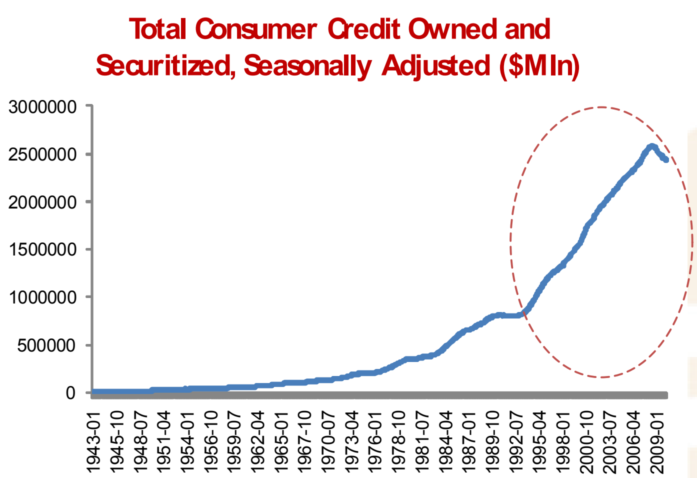

Figure 5

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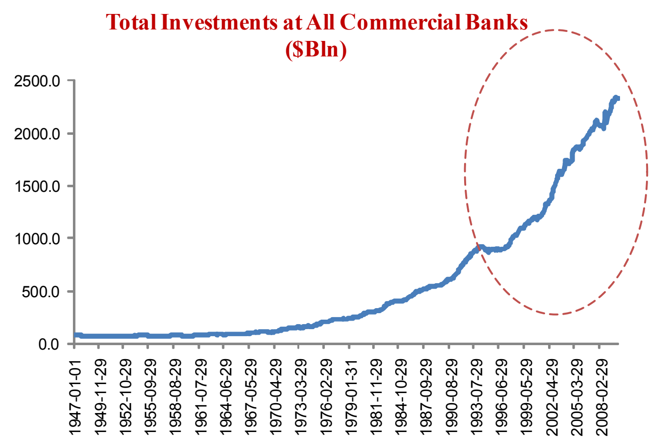
Figure 6



Source: Federal Reserve Bank of St. Louis

The nature of the 2008 financial failure was the clash of conflict or impenetrable forces of contradiction between the investors' belief in a free market system and a popular idea of massive homeownership. This extreme version of the infusion of a democratic idea in a capitalism system had not only caused serious collision of beliefs and short-circuited the entire financial structure but also shattered confidence, trusts, and other important psychological factors that intensified the downturn – it was the fear of loss or out of control that had prompted investors to pull out of their funds that initially caused liquidity failure and eventually the system collapse. While we know that subprime population could not resist the idea of homeownership but had a track record of defaults that will not change, we also know that many had invested their savings or leveraged funds with higher returns but would withdraw funds when risk becomes too large. As the belief in a free and efficient market system had bypassed these market movements, behavioral finance could have detected many symptoms, such as overconfidence, mental framing, and herding behavior, early enough to prevent a great recession from numerous excesses through regulations and policies.

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Proposition 4: *The psychological tipping point that led to crashes*

During the boom time, stock values were overvalued with P/E ratios well into the double digits. Yet some argue that not all bubbles burst. During the 1960-72 periods, P/E ratios were high for stocks but there was no crash occurred. Nonetheless and in retrospect, asset prices went from overvaluation to undervaluation without stopping at fair value during almost all boom and crash cycles. This is because human decisions were made based on both rational and emotional factors or from reasoning and perception/intuition (Kahneman, 2002). The over/under-reactions occur when emotions dominate rationality under particular market conditions and with signals of doubts. The abrupt switch from risk seeking to risk aversion can also be explained by reference-dependence in prospect theory when decisions or preferences were made based on particular reference point. Given these behavior, we may conclude that psychological factors, such as over-optimism and over-pessimism according to study results (Kent and Hirshleifer, 1998), played important roles in contributing to the economic shocks beyond the EMH could explain.

These symptoms of investor behavior observed from data were further triggered by innate human characteristics of greed, fear, and herding that played out under various external conditions. In addition and in the 2008 crash case, external factors were significant influences on the magnitude of investor behavior due to volumes of trades, the nature and the structures of financial products and other market conditions at the time. Between 2007-2008, household debt was 98%-97% ($13.8Tril) of GDP and the assets of top banks involving subprime lending accounted for 63% of GDP by 2010 compared only 17% in 1995. While these debts accounted for about 75% of all loans on the book for traditional financial institutions in 1958, only 18% of all loans were on the book while the majority was sold to investors. Meanwhile, consumer and corporate lending increased about 48% compared with that for government during the same period. More critically, these capital growths were not from productive uses for real growth – loans were made to households that could not afford to make payments or risk spreading for unsellable homes and empty shopping malls.

3. Characteristics of Cognitive Limitations as Drivers of Asset Prices Excesses

The following graph illustrates some of the mechanisms between how humans process information and the behavioral outcome.[2]

Cognitive/Emotional Needs/Desires Of Market Participants	Mental Information Processing Mechanics	Behavioral Outcomes
Need for Sense of Control	• Pay-off Rationale • Self-Attribution • Framing • Heuristics	• Over/Under-Confidence • Pessimistic/Risk Aversion • Myopic Behavior • Herding
Decision/Desire to Gamble	• Magical Thinking	• Optimistic & Risk Taking • Herding

There are many shared characteristics among humans outplayed in the market typically greed and fear that exacerbated the severity of economic cycles. To many, the classical rational models had not only excluded human emotions, preferences, and other personal sentiments, but also were too demanding for most people to attain results required in the assumptions in the models: people are not accustomed to thinking hard and are often content to trust a plausible judgment that quickly comes to mind (Kahneman, 2002). Combining psychology and physiology, neuroscientists had concluded that humans utilize both the reasoning/logical part (the prefrontal cortex) as well as the emotional side (the Anteria) of the brain during the

[2] See footnote at end for definitions of framing, heuristics, and others.

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decision-making process. While humans have limited cognitive reasoning due to lack of mental efforts, habits, and capacity and biased cognitive intuition affected by accessibility, heuristics, and framing during the decision-making process, the rational model lost its effectiveness and power in predicting and controlling the economy and the financial market because of its negligence to the very foundation and mechanics of how human minds, brains, and emotions work for the majority of the population. In addition, many of these human factors were especially transparent and exacerbated because of shared characteristics of human nature and desires under certain conditions such as changes in rules and regulations.

While the standard theory of choices includes individual preferences with extensionality[3] and information changes in addition to income and price changes, behavioral and neuroeconomic theories of choice extend that decisions can be influenced by all other exogeneous factors that can influence decision-making process. These exogeneous factors could include one's particular life experience that influence his/her perceptions and values in addition to genetic determinants that ultimately affect his/her judgments and choices. Thus, in addition to various constraints, limitations, and instability of mental capacities and emotions shared by most humans, there are imperfect market dynamics with personal interpretations, whether they are information asymmetry, a diverse pool of analysts' subjective opinions that affect market penetrations, market complications and ambiguities, uncertainties due to globalization and inconsistency in regulations.

While technology advancement had benefited many, it also has side effects to some. As humans can only absorb so much information along with other cognitive limitations, a market with super complexity not only contributes judgment biases, but also sows seeds for greater

[3] See notes at the end.

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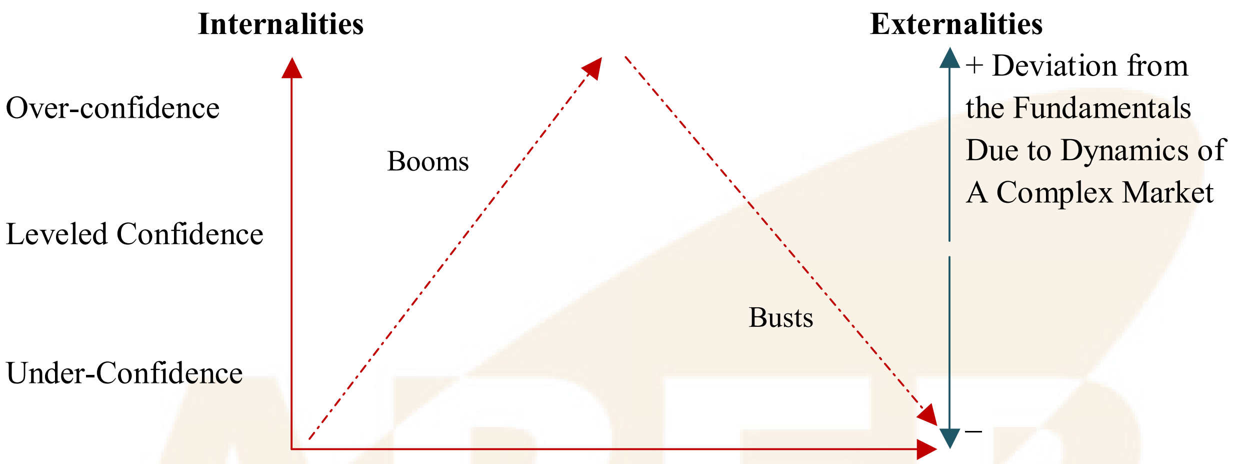
catastrophe as we just experience because of the interconnectedness and other market mechanisms that modern technology is capable of in an advanced economy. The graph below shows the interactions of how human behavior and external factors contribute to the booms and busts of economic cycles.

Figure 7



Pursuit of Profit with Need for feeling of Control/Desire to Gamble via Syndromes of Pay-off Rationale, Self Attribution, Anchoring, Risk Aversion, Herding, etc.

4. The Model and Related Literatures – A Multilateral Approach with Neural Networks and Feedback Loops

In addition to an imperfect regulatory and policy system in development and a complex and uncertain global industrialization, the causes of recent booms and busts were also attributed to many theoretical assumptions, such as the efficient market hypothesis (EMH) and the Rational Expectations Theory (RET) where the asset price P is defined as

$$P = P^* + \varepsilon \qquad \textit{And} \qquad P^* = E(P) \qquad\qquad (1)\ \&\ (2)$$

These hypotheses and theories had dominated market beliefs in deregulation, risk management, and valuation systems for the last five decades. In addition, the free market concept grew out of these theories had served as stimuli for new financial products in pursuit of

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hypothetical growths and investment opportunities on the one hand and as potential for catastrophic failures on the other due to unforeseen consequences of what a complex product would entail given human cognitive limitations and intrinsic nature that ultimate led to poor judgments and biased behaviors during the outplay of the market.

Other related models, such as the capital asset pricing model (CAPM) where

$$E(R_i - R_f)/B_i = E(R_m - R_f), \tag{3}$$

were based on narrow assumptions such as normal distributions that ignored investor preference yet worked in contradiction with EMH when assets with low beta give higher returns.

While the ruling paradigm of financial economics with EMH and CAPM were over simplified and linear or bilateral in nature, we propose a non-linear model with multi-agents of reflexive and ambiguous characteristics in the economy that determines the real capital asset pricing in the market that ultimately led to the magnitude and frequency of economic booms and busts given regulatory and market conditions and externalities.

Given the interconnectedness of multiple agents in the complex market, we propose a model using neural networks techniques to investigate the impact of specific inputs, such as deregulation and innovations represented by asset prices in real estate, technology, and financial sectors and human factors in the hidden layer represented by various fear, confidence, and other indices, on the output which is the asset price using the S&P 500 Index.

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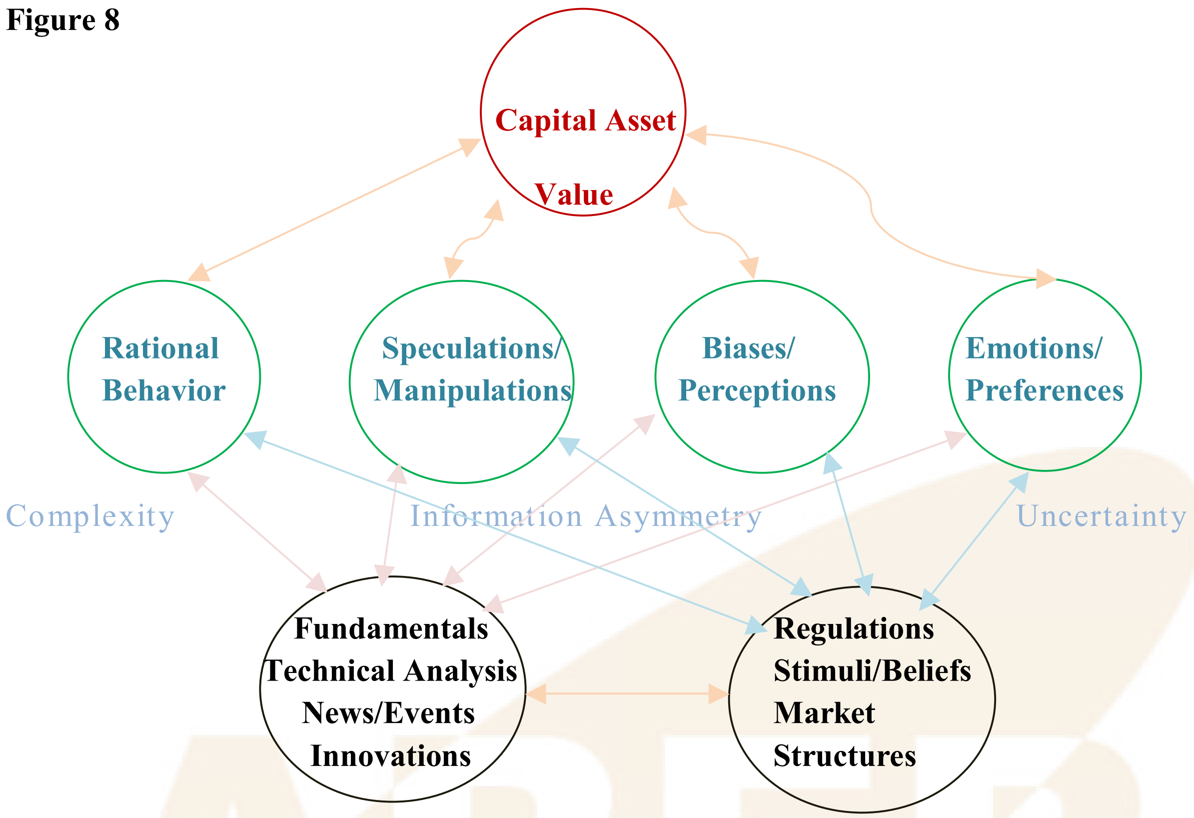
Figure 8



The neural network approach used here tries to extract regularities in the financial data around the boom and bust periods that are associated with psychological characteristics of investors and fund managers discussed in the previous sections. We propose a two-tier layer of network utilizes weight-sum units *w* with the output function $f = g(w'x + b)$, where *g* was a logistic function or sigmoid where the output varies continuously but not linearly as the input changes. The *x* represents the data series and the horizontal axis of *b*. The bottom two factors in the graph above represent the input layer. The human factors in the middle were the hidden layer and the capital asset price or value is the output layer. There are no limitations on the type of algorithm used for learning.

The model assumes a feedback loop characteristic since there are many players in the market and actions taken or options made by the decision makers were based upon the concept of

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"decision frame" (Tversky and Kahneman, 1981) which involves conditional probabilities, factors that dependent on the market condition before actions taken as well as the expected outcomes of the action taken by oneself and those of other market players and so on and so forth. The outcome of the feedback loop at any point is further controlled by various forces among different players; some based on their decisions according to the highest expected utility (the rational decision-makers) while others may be influenced by their personal habits and sentiments (the biased and emotional decision-makers) and there are the market manipulators and speculators with incomplete information in an imperfect market who are ready to take more risks under stressful market environment.

The hypothesis in reduced form to be tested is

$$E\ (V_t \mid N_{t-1}) = \alpha\Delta U_t + \beta\Delta D_t + \varepsilon_{t-i}, \tag{4}$$

where

$$E(\Delta U_{t,}) \mid \alpha\Delta E_{t-i} + \varepsilon_{t-i} \text{ and } E(\Delta D_t) \mid \alpha\Delta E_{t-i} + L_t + \varepsilon_{t-i}, \tag{5}$$

where

$$\Delta E_t \mid \lambda\Delta T_t + \sigma I_t + \beta\Delta R_t + \varepsilon_{t-i}, \tag{6}$$

And

$$D_t = P^b{}_t / P_{t.} \tag{7}$$

D = behavior dispositions conditional on market externalities with biases
L = cognitive limitations and bias such as overconfidence or anchoring
E = macroeconomic economic factors
R = regulation disturbance
T = technology interruptions
I = innovation shocks
N = news to the market
P = price of an asset under normal condition
P^b = price of an asset under biased condition
U = unbiased behavior which can be represented by present value of consumption level

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V = value of capital asset
Subscript $_{it}$ denotes price or return of asset i at specific time period t.

We follow the McCulloch and Pitts model (MCP) where weights were used to gauge the effect of the input and hidden layers have on decision-making. The process sums up the weighted inputs and determine their impact on the output when a pre-set threshold value is violated. A key feature of the MCP neuron is that it allows adaptation of weights such as the back error propagation that is used in recurrent back propagation or feedback loop networks. Feedback networks are dynamic and change continuously in both directions until they reach an equilibrium point. A new equilibrium needs to be found when input changes.

There are three phases in the neural network modeling process - training, cross validation, and testing. The training process teaches the network what the underlying relationships between the input and output variables are or what characteristics in an input variable are attributable to the output variable. The cross validation process saves the weights that gave the best results while minimizes errors. The testing process generates results in the modeling with new data applying what previous processes in training and cross validation had learned and saved.

5. Dataset and Statistical Methods

Basic economic variables and major regulatory, technology, and other stimulus policy changes are considered to be the input variables. In this model, the hidden layer is composed of human factors both in rational and emotional forms. These variables are determined by the changes in the input variables as a response and the weights on the connections between the input and the hidden variables. Subsequently, the behavior of the output, the asset price in this

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case, depends on the movement of the hidden layer and the weights between the hidden and output variables.

In addition, the hidden layer can be modified to determine when it is active as the weights between the input and hidden layers are adjusted. So by adjusting these weights, the hidden layer can choose what it represents; though adjustments need to be backed by explanations.

All data were converted from nominal to real using Consumer Price Index with base year of 2010. These real numbers were transformed to natural log and the differences of the natural log from the previous period were used for modeling.[4]

The output or dependent variable is the S&P 500 asset price in time series. Multiple layers of input or independent variables were selected representing the baseline economy or those according to the efficient market theory, the earnings and dividend per share of the S&P 500 Index, the present dividend values of the S&P 500 index discounted by constant discount rate, the interest rate, the marginal rate of substitution in consumption (Shiller, 2003), GDP, and aggregation consumption level, etc. Total consumer credit outstanding, which includes all consumer debts and loans secured and unsecured, was selected as a reflection of deregulation since the late 1970s or the elimination of the Glass Steagall Act in 1999. Three sentiment indices, the Barron's Confidence Index (BCI)[5], the Volatility Index (VIX)[6], and the Consumer Confidence Index (CCI) from the University of Michigan represent the human factors outlined in previous sections and the cognitive limitations of the market participants. These variables were

[4] See footnotes at the end.
[5] See footnotes at the end.
[6] See footnotes at the end.

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tested under the hidden layer in a multilayer perceptron architecture[7] of the neural network model to determine whether and to what extent these variables contribute to the variations of the S&P 500 Index.

Panel data were used to investigate the impact of the variables selected before and after the effect of the booms and busts and enable measurement of factor sensitivities of an asset at the aggregate level with and without market innovations or shocks. The periods are defined as the dotcom and subprime crises using data ranging from 1995-2010, the post deregulation period from 1986-2010, where the sentiment related indices became available. Data were also divided between post- and prior- recession periods to gauge the significance of the fundamental measures on the asset price. Different innovations in technology and other financial products developed under various policy changes were implied during these defined periods. Weekly, monthly, and yearly were used and sentiment data were available since 1986.

Model variables were tested on the actual S&P 500 Index as well as the excesses or the difference between the actual market data and that the efficient market hypothesis or the rational theory prescribes. Models on market excess test the significance of the impact of the selected variables on the residual price, an estimation of anomaly, compared with those on the actual market.

As Akelof and Shiller noted (2010), the economic expansion and contraction in the modern world tend to be worldwide phenomena. Given the influence of the US market on the global market, indices from international markets, such as the FTSE 100 in Europe, the Hang Seng Index in Hong Kong and the Nikkei Index of Japan were compared with the S&P 500

[7] See notes at the end.

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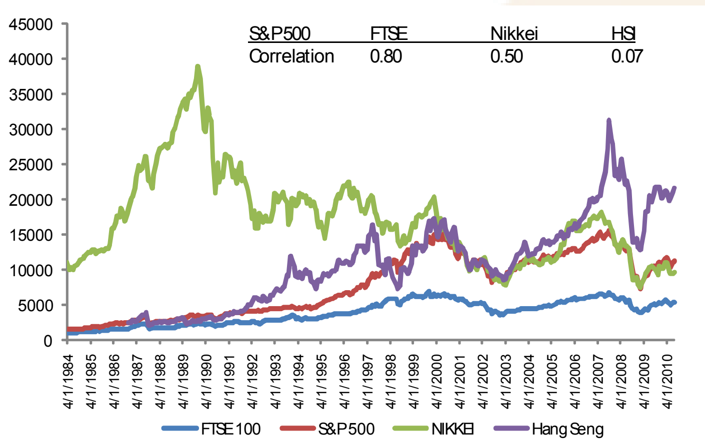
index in terms of their performances (see Figure 9 below). While the underlying factors attributable to the index performance, such as regulation change and market sentiment, may vary given differences in domestic policies and cultural and country specific variations that determine the level of rationality and investor sentiments in a market, a severe market shock as the financial crisis we just experience is expected to have meaningful impact on the world market due to the global transformation of human labors and skills, multinational entities, market concepts, trades, technologies, and product innovations, in addition to shared human factors such as emotion and cognitive limitations.

Figure 9



Source: Yahoo Finance!

6. Model Results and Interpretations

Models were run and categorized in three types (1) the sentiment based models were regressed with sentiment variables (2) the fundamental variables using technical measures such as dividend and earnings per share and (3) the combined models apply variables of both types above in investigating the impact of the these variable on the asset price. The tables below summarize the results.

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Models of Sentiments

Table 1-2

1986-2010
Weekly data with Linear Regression

	Training	Cross Val.	Testing	Wtd Avg.
# of Rows	644	161	268	1,073
MSE	0.00025	0.00026	0.00048	0.00000
Correlation (r)	0.67126	0.65540	0.69820	0.67561
Min Absolute Error	0.00005	0.00002	0.00005	0.00000
Max Absolute Error	0.07657	0.06361	0.14183	0.00018
Mean Absolute Error (MAE)	0.01196	0.01114	0.01378	0.00000

1995-2010
Monthly data during cycle years with Radial Basis Regression

	Training	Cross Val.	Testing	Wtd Avg.
# of Rows	108	27	46	181
MSE	0.00096	0.00038	0.00149	0.00000
Correlation (r)	0.60156	0.64301	0.68062	0.62783
Min Absolute Error	0.00023	0.00026	0.00135	0.00000
Max Absolute Error	0.11051	0.03974	0.09599	0.00087
Mean Absolute Error (MAE)	0.02504	0.01596	0.02948	0.00000

Notes: Sentiment models include variables of Consumer Confidence Index, Barron's Confidence Index and the Volatility Index. Only models with the best results are reported. Experimental models include linear regression, radial basis function, multilayer perceptron, general feedforward network, time-delay network, time-lag recurrent network, recurrent network, etc. See detailed outputs in appendix.

Models of Fundamentals

Table 3-4

1986-2010
Monthly data using Multilayer Perceptron Method

	Training	Cross Val.	Testing	Wtd Avg.
# of Rows	172	44	72	288
MSE	0.001379	0.002189	0.001755	0.00000
Correlation (r)	0.022409	-0.075999	0.312991	0.08002
Min Absolute Error	2.65E-05	8.73E-05	0.002947	0.00000
Max Absolute Error	0.141419	0.115671	0.200982	0.00020
Mean Absolute Error (MAE)	0.028838	0.037057	0.031875	0.00000

1995-2010
Monthly data during cycle years using Multilayer Perceptron

	Training	Cross Val.	Testing	Wtd Avg.
# of Rows	108	27	46	181
MSE	0.001019	0.0004533	0.001907	0.00000
Correlation (r)	0.57234	0.2973507	0.623519	0.54433
Min Absolute Error	8.04E-05	0.0033239	0.000483	0.00000
Max Absolute Error	0.095036	0.044472	0.112769	0.00076
Mean Absolute Error (MAE)	0.025336	0.0183768	0.033922	0.00000

Notes: Fundamental models include variables of dividend and earnings per share of the index, 10-year Treasury Maturity Rate, consumer credit and loans outstanding, investments, mortgage backed securities, and other real estate loans reflecting structural changes in regulation and market innovations.

Combined Models

Table 5-6

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1986-2010

Monthly data using Radial Basis Function

	Training	Cross Val.	Testing	Wtd Avg.
# of Rows	172	44	72	288
MSE	0.000912	0.002049	0.001529	0.00000
Correlation (r)	0.403294	0.264807	0.592965	0.42955
Min Absolute Error	5.72E-05	0.00112	0.000254	0.00000
Max Absolute Error	0.14101	0.12418	0.133575	0.00059
Mean Absolute Error (MAE)	0.021167	0.035283	0.028292	0.00000

1995-2010

Montly data during cycle years using Linear Regression

	Training	Cross Val.	Testing	Wtd Avg.
# of Rows	112	28	47	187
MSE	0.001039	0.0005138	0.001508	0.00000
Correlation (r)	0.545213	0.5976725	0.687595	0.58885
Min Absolute Error	0.000391	0.000145	0.000659	0.00000
Max Absolute Error	0.103861	0.0680844	0.113278	0.00094
Mean Absolute Error (MAE)	0.025309	0.0160308	0.027999	0.00000

Notes: Variables in the combined models include those in the models of the fundamental and sentiments.

Models of Residual Price and Policy Impact

Table 7-8

1990-2010

Montly data with residual price using Multilayer Perceptron

	Training	Cross Val.	Testing	Wtd Avg.
# of Rows	144	36	60	240
MSE	0.00135	0.00056	0.00130	0.00000
Correlation (r)	0.27635	0.81732	0.66492	0.45464
Min Absolute Error	0.00003	0.00001	0.00043	0.00000
Max Absolute Error	0.11085	0.04339	0.11069	0.00058
Mean Absolute Error (MAE)	0.02787	0.02077	0.02664	0.00000

1986-2010

Montly data policy impact on investment using generalized feedforward

	Training	Cross Val.	Testing	Wtd Avg.
# of Rows	172	44	72	288
MSE	5.34E-05	0.000114	0.000137	0.00000
Correlation (r)	0.429815	0.220347	0.434514	0.39899
Min Absolute Error	2.79E-05	0.000851	1.42E-05	0.00000
Max Absolute Error	0.032129	0.025673	0.032807	0.00012
Mean Absolute Error (MAE)	0.005569	0.008964	0.009379	0.00000

Notes: Residual price is the market price minus dividends and earnings representing the estimation of market anomaly. Only sentiment variables were used in the regression. In the policy model, real estate loan outstanding is most correlated with total investments. Other variables used are consumer credit and mortgage backed securities.

Models using sentiment variables gave the most stable and best results in terms of correlation and prediction of asset price represented by the S&P 500 Index in the linear regression and neural network modeling frame. The fundamental model gave poor projection in Table 3 due to low price correlation with fundamental variables. Nonetheless, the fundamental model in Table 4 improved during cycle years due to increased correlation with the earnings variable (see Table 10 below). The combined models give better forecasts than those using fundamental variables only because of the sentiment factors.

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The residual price model in Table 7 has the best projection in cross validation data during cycle years entailing that price anomalies are more correlated with market sentiments than the fundamentals[8]. See tables below for correlation and sensitivity analysis.

Correlation and Sensitivity Analysis

Table 9-10

1995-2010

Sentivity and Correlation between dependent and independent variables

S&P 500	Sensitivity @ Mean	Correlation Analysis
Dividend	0.0379	-0.01
Interest	0.0375	0.1
Earnings	0.0215	0.3
Credit	0.0062	0.07
Investments	0.0113	-0.11
RE Loans	0.0061	-0.08
MBS	0.0093	0.05
CCI	***0.0605***	***0.42***
BCI	***0.0349***	***0.39***
VIX	***0.0072***	***-0.34***

Price correlation with fundamentals across time

S&P 500	1890-1948	1949-2010	1947-1978	1979-2010	1986-1997	1998-2010
Dividend	0.56	0.28	0.05	0.03	0.13	-0.03
Earnings	0.49	0.2	-0.02	0.21	-0.06	0.31
Interest	-0.71	-0.65	-0.08	-0.07	-0.33	0.16

Table 11-13

Price sensitivity and correlation with fundamentals

	1871-1939		1940-1979		1980-2010	
S&P 500	Sensitivity @mean	Correlation Analysis	Sensitivity @mean	Correlation Analysis	Sensitivity @mean	Correlation Analysis
Dividend	0.0027	0.11	0.0008	0.09	0.0040	0.03
Earnings	0.0744	0.16	0.0402	0.03	0.0579	0.21

Price sensitivity and correlation with market sentiments

	1986-1997		1998-2010	
S&P 500	Sensitivity @mean	Correlation Analysis	Sensitivity @mean	Correlation Analysis
CCI	0.0751	0.26	0.0753	0.45
BCI	0.0372	0.01	0.0502	0.41

Price sensitivity and correlation with MBS before and after deregulation

Mortgage backed securities

S&P 500	Sensitivity @mean	Correlation Analysis
1970-99	0.0024	0.03
2000-10	0.0022	0.06

[8] See footnote at the end.

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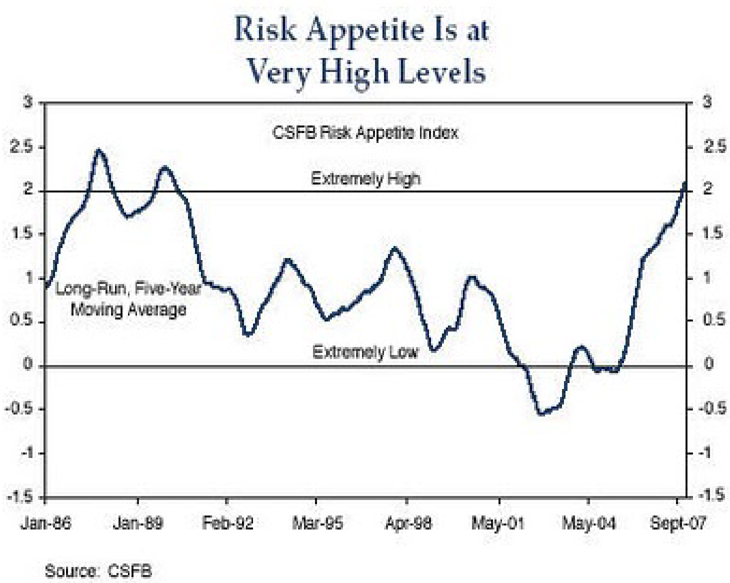
From the analysis tables above, sentiment related variables such as the Consumer Confidence Index, the Barron's Confidence Index, and the volatility index had stronger correlation with the market dynamics in the past decade. The Risk Appetite Index in 5-year moving average below, which is another market sentiment variable, showed a striking increase prior to the 2008 crisis that further made the case in point.[9]

Figure 10



7. Concluding Remarks

The study showed that changes in regulation, technology development, and industry innovations since the 1990s had made striking imprints in the financial market and changes in population disposition in the investment space in an economy in terms of trading volumes, volatilities, and asset prices represented by the S&P 500 Index as illustrated in Figure 1A and

[9] See footnote at the end.

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Figure 4-6. Nonetheless, these extraordinary movements shifted further away from the fundamentals defined by the performance of the asset and the economy, such as dividend and interest rate, and more in tune with human sentiments measured by confidence and volatility indices. Indeed, human emotions and biases due to cognitive limitations had not only dominated the market in the past decades, but also intensified the effects of the expansions and contractions in the economy driven by deregulation and other industry development in a free market system in the context of a dynamic global market as shown in the qualitative analyses in the study and quantitative evaluations in the neural network modeling. While the current crisis had made few better off, it had severely damaged the life qualities of the majority of the population worldwide with lasting adverse consequences because of differed motivational dynamics and behavioral structures between the financial industry and the rest of the economy.

With a complex market, technology advancement, global economic development and the interconnectedness given limited modulations occurred in the development of human nature, cognitive abilities, and emotions, the EMH and other modern financial theories had served more as an ideology or what the market should be in a normative economy than what the market actually has been in a positive economy under a capitalistic and free-market system. Without proper government intervention, efficient market cannot be achieved due to variations of human factors. In other words, reality does not coincide with the general equilibrium theory in an economy without appropriate regulations reining the excesses from human behavior.

8. Regulatory and Policy Implications

In addition to human nature, such as greed and fear that had dominated the financial markets across the global for decades, cognitive biases will continue to exist due to imperfect

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human perceptions, limitations of the physical functionality of human brain, and its capacity and interactions with dynamic and increasingly complex externalities. And these imperfections were fundamental causes of economic booms and busts that recur throughout human history. Moreover, the speed of technology development had not only exceeded that of the human development in cognitive terms, but also debilitated us from making sound judgment to some extent given the volume, speed, and sometimes the quality of information that are forced upon us. In today's business and economic environment, it is beyond the capacity of the majority of individuals in meeting the market demand in the decision making process independent of herd behavior while interacting with consequences of collective efforts in the market whether they are informational or technological at the global scale.

Given the recurrence of severe financial crises and the ramifications of these events on the global economy and people's lives caused by similar conditioned stimulus factors in recent history, operant conditioning, a learning theory introduced by Edward L. Thorndike, may be applicable from a behavioral point of view as a remedy for preventing future crises caused by observed behavior in the financial and other industries.

According to the law of effect by Edward Thorndike, "of several responses made to the same situation, those which are accompanied or closely followed by satisfaction to the animal will, other things being equal, be more firmly connected with the situation, so that, when it recurs, they will be more likely to recur; those which are accompanied or closely followed by discomfort to the animal will, other things being equal, have their connections with that situation weakened, so that, when it recurs, they will be less likely to occur" (Thorndike, 1911). Or in B. F. Skinner's term, when a reinforcer presented after a response as a stimulus, it leads to an increase in the future rate of that response.

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In relation to the market behavior during an economic cycle, investor responses to economic activities were pro-cyclical which intensified a boom or a bust condition. Given human behavior and the law of effect, the case of deregulation and other financial policies with fewer restrictions before the crisis had indeed provided more opportunities as stimuli in exacerbating the booms and busts of economic cycles. On the other hand, subprime lending, which triggered the current crisis, was a stimulus in defect in particular when borrowers were unable to repay debts and lenders or investors were afraid of losing investments.

Applying the operant condition theory, which describes how the distribution of probabilities in a population of stimuli-response connections varies overtime as a function of specified environmental variables, counter-cyclical regulatory policy can be applied to transform human behavior and biases. One example of counter-cyclical policies would be to increase capital requirements of firms during expansion periods and reducing them during contraction.

In addition to establishing rules that restrict excessive and abusive behavior among individuals and institutions while improving industry standards, rational behavior, which would bring market to its equilibrium as the efficient market hypothesis presumes, should be encouraged through learning, distribution of quality information, and long-term investing that contributes to real productivities of an economy. While we have observed that investor sentiment had led the market in recent decades due to regulatory shifts, transformation of global economy, and other externalities, rational behavior still exists, though among smaller groups, in the investment community. Policies modulate to advance more rational behavior consistent with the incumbent economic and political systems are expected to strengthen the efficiency of the market.

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Footnotes:

[1] Limitations of arbitrage refer to the limits of correction forces or arbitraging away the difference between the market price and that of fundamentals dictate due to various restrictions.
[2] Overconfidence occurs when the individual believes s/he knows or has the ability more than s/he actually does/has while shows little evidence supporting his/her belief. Overconfidence intensifies when perception of control increases. Overconfidence can turn into under-confidence quickly or occur simultaneously when market does not deliver the same result as expected due to the need of the perception of control – the behavior of a pessimist or risk-aversion. Anchoring refers to a mental characteristic that disproportionate weighs on the first or the most recent information received. It is an extreme version of the heuristics and the main cause of under- or overconfidence given the "stickiness" nature of the mental attribute. Framing results from preferences that are affected by variation in description, e.g., how words are used to frame certain preferences. Heuristics include availability, representativeness, and anchoring.
[3] According to Kahneman (2002), extensionality assumes that preference is not affected by negligible variations in the description of outcomes.
[4] Data sources include the Federal Reserve Bank, Bureau of labor statistics, the bureau of economic analysis and the Census. Market data were acquired through *Yahoo!Finance*, the Barron's, and Robert Shiller Online Data of the Yale School of Management.
[5] Barron's Confidence Index is the average yield of a high-grade bond divided by the average yield of an intermediate-grade bond indicating returns investors demand given perceived levels of risks.
[6] Volatility Index is also an indicator of level of fears and has a negative relation with the S&P 500 in general.
[7] Multilayer perceptron consists multiple layers of input and output nodes and detects data that are not linearly separable. It is a feedforward neural network model and each neuron comes with a nonlinear activation function.
[8] The first 144 data points span from 1990-2001 and the next 36 data points represent years of 2002-2004.
[9] The Risk Appetite Index measures the level and volume of investors' appetite in taking risks given asset performance. Abnormal risk taking or aversion moves asset price away from its fundamentals. The index is not included in the model due to data unavailability.

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Appendix

Table A1

The weekly sentiment model 1986-2010

Performance Metrics

Model Name	Training MSE	Training r	Training MAE	Cross Validation MSE	Cross Validation r	Cross Validation MAE	Testing MSE	Testing r	Testing MAE
LR-0-B-L (Linear Regression)	0.00025	0.67126	0.011964	0.000257	0.655402	0.011145	0.000481	0.698198	0.013781
MLP-1-B-L (Multilayer Perceptron)	0.000254	0.664569	0.012074	0.000363	0.491997	0.012679	0.000552	0.627818	0.014307
PNN-0-N-N (Probabilistic Neural Network)	0.000207	0.739867	0.010941	0.000409	0.428211	0.013667	0.000703	0.485901	0.01559

Table A2

The monthly cycle period model 1995-2010

Performance Metrics

Model Name	Training MSE	Training r	Training MAE	Cross Validation MSE	Cross Validation r	Cross Validation MAE	Testing MSE	Testing r	Testing MAE
LR-0-B-L (Linear Regression)	0.001107	0.510247	0.026763	0.000248	0.7305	0.012584	0.001838	0.602808	0.031862
MLP-1-B-L (Multilayer Perceptron)	0.000991	0.591532	0.025785	0.000325	0.638868	0.014371	0.001562	0.651852	0.030501
PNN-0-N-N (Probabilistic Neural Network)	0.00139	0.523553	0.028682	0.000407	0.697827	0.016323	0.002345	0.707247	0.034308
RBF-1-B-L (Radial Basis Function)	0.000955	0.601556	0.025044	0.000385	0.643009	0.015965	0.001494	0.680616	0.02948
GFF-1-B-L (Generalized Feedforward)	0.001085	0.527909	0.02654	0.000266	0.717603	0.012974	0.001722	0.619058	0.031728
MLPPCA-1-B-L (MLP with PCA)	0.001287	0.392718	0.028119	0.000373	0.556924	0.015506	0.002118	0.520715	0.034658
SVM-0-N-N (Classification SVM)	0.001386	0.675696	0.028036	0.000694	0.535408	0.021962	0.002975	0.382741	0.0352
TDNN-1-B-L (Time-Delay Network)	0.000795	0.732834	0.022939	0.000463	0.553629	0.016033	0.002512	0.463831	0.032587
TLRN-1-B-L (Time-Lag Recurrent Network)	0.001314	0.479325	0.029974	0.000727	0.561919	0.022058	0.00242	0.439903	0.037992
RN-1-B-L (Recurrent Network)	0.001258	0.482547	0.029	0.00058	0.574841	0.019791	0.002527	0.507487	0.038353
MLP-2-B-L (Multilayer Perceptron)	0.001111	0.518086	0.026979	0.000252	0.721116	0.012857	0.001852	0.587009	0.030564

Table A3

The monthly residual price model 1990-2010

Performance Metrics

Model Name	Training MSE	Training r	Training MAE	Cross Validation MSE	Cross Validation r	Cross Validation MAE	Testing MSE	Testing r	Testing MAE
LR-0-B-L (Linear Regression)	0.001117	0.329533	0.025696	0.001298	0.553753	0.026174	0.00184	0.498154	0.02938
MLP-1-B-L (Multilayer Perceptron)	0.001385	0.331393	0.028787	0.000822	0.787596	0.024366	0.001508	0.63789	0.030398
PNN-0-N-N (Probabilistic Neural Network)	0.001224	0.404971	0.025713	0.001568	0.741951	0.030165	0.002127	0.546255	0.031241
RBF-1-B-L (Radial Basis Function)	0.000994	0.454844	0.024169	0.001374	0.579402	0.029194	0.001555	0.613922	0.029333
GFF-1-B-L (Generalized Feedforward)	0.001048	0.516491	0.024727	0.00106	0.627842	0.025898	0.002085	0.544922	0.03464
MLPPCA-1-B-L (MLP with PCA)	0.001351	0.276346	0.027871	0.000558	0.817321	0.020768	0.001304	0.664918	0.02664
SVM-0-N-N (Classification SVM)	0.001368	0.578519	0.02837	0.002148	0.276188	0.036065	0.002781	0.272737	0.034714
TDNN-1-B-L (Time-Delay Network)	0.000615	0.7202	0.01922	0.001403	0.566169	0.031359	0.002991	0.368562	0.036998
TLRN-1-B-L (Time-Lag Recurrent Network)	0.001321	0.319884	0.029874	0.001588	0.489679	0.033224	0.003888	0.149711	0.042928
RN-1-B-L (Recurrent Network)	0.001046	0.518385	0.026244	0.000891	0.734027	0.024131	0.001654	0.646598	0.031511
MLP-2-B-L (Multilayer Perceptron)	0.001103	0.365033	0.026067	0.001115	0.693604	0.025753	0.001586	0.610541	0.027782

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Table A4 - The monthly fundamental model 1986-2010

Performance Metrics

	Training			Cross Validation			Testing		
Model Name	MSE	r	MAE	MSE	r	MAE	MSE	r	MAE
LR-0-B-L (Linear Regression)	0.000979	0.317637	0.021126	0.003175	-0.33503	0.044725	0.00497	-0.37944	0.044341
MLP-1-B-L (Multilayer Perceptron)	0.000973	0.352588	0.022325	0.002858	-0.13782	0.042322	0.002854	-0.04321	0.034712
PNN-0-N-N (Probabilistic Neural Network)	0.001021	0.401814	0.02289	0.002376	-0.23072	0.037689	0.002029	0.015696	0.030244
RBF-1-B-L (Radial Basis Function)	0.000902	0.414383	0.020468	0.002714	-0.24768	0.041295	0.002119	-0.01806	0.030644
GFF-1-B-L (Generalized Feedforward)	0.001003	0.28583	0.021285	0.002872	-0.38181	0.042509	0.002332	-0.09145	0.031573
MLPPCA-1-B-L (MLP with PCA)	0.001264	0.290562	0.026719	0.001983	0.073363	0.034582	0.002323	-0.06827	0.035686
SVM-0-N-N (Classification SVM)	0.003302	0.420156	0.050347	0.004231	-0.13632	0.051852	0.003674	0.128791	0.047825
TDNN-1-B-L (Time-Delay Network)	0.001357	0.18065	0.027407	0.002462	-0.02152	0.038695	0.00204	0.270431	0.033533
TLRN-1-B-L (Time-Lag Recurrent Network)	0.001552	0.068993	0.030598	0.002452	0.201894	0.037817	0.002676	-0.02672	0.035669
RN-1-B-L (Recurrent Network)	0.001812	-0.15785	0.033017	0.003328	-0.13345	0.045457	0.003579	0.205864	0.045814
MLP-2-B-L (Multilayer Perceptron)	0.001379	0.022409	0.028838	0.002189	-0.076	0.037057	0.001755	0.312991	0.031875

Table A5 - The monthly fundamental cycle period model 1995-2010

Performance Metrics

	Training			Cross Validation			Testing		
Model Name	MSE	r	MAE	MSE	r	MAE	MSE	r	MAE
LR-0-B-L (Linear Regression)	0.001396	0.25949	0.029484	0.000639	0.262268	0.019936	0.002527	0.337413	0.035342
MLP-1-B-L (Multilayer Perceptron)	0.001268	0.42112	0.028498	0.000458	0.369062	0.017319	0.00261	0.365813	0.035761
PNN-0-N-N (Probabilistic Neural Network)	0.001453	0.339095	0.02897	0.000525	0.29524	0.018859	0.002584	0.245488	0.035921
RBF-1-B-L (Radial Basis Function)	0.001313	0.349981	0.02803	0.000692	-0.0863	0.021312	0.002588	0.259803	0.035211
GFF-1-B-L (Generalized Feedforward)	0.001477	0.442943	0.030852	0.000426	0.317178	0.016802	0.004786	0.116098	0.048362
MLPPCA-1-B-L (MLP with PCA)	0.001324	0.363493	0.028908	0.000445	0.256757	0.017345	0.002934	0.043263	0.037539
SVM-0-N-N (Classification SVM)	0.001394	0.682809	0.027477	0.000826	0.015029	0.024451	0.003026	0.241912	0.036154
TDNN-1-B-L (Time-Delay Network)	0.001915	0.041906	0.032479	0.000879	0.09809	0.023338	0.005029	0.028046	0.053926
TLRN-1-B-L (Time-Lag Recurrent Network)	0.001367	0.385113	0.029375	0.000519	0.114982	0.019408	0.002641	0.380266	0.036523
RN-1-B-L (Recurrent Network)	0.001595	0.071399	0.02982	0.000949	0.109909	0.024967	0.004522	-0.28009	0.05
MLP-2-B-L (Multilayer Perceptron)	0.001019	0.57234	0.025336	0.000453	0.297351	0.018377	0.001907	0.623519	0.033922

Table A6 - The monthly model on policy impact of investments 1986-2010

Performance Metrics

	Training			Cross Validation			Testing		
Model Name	MSE	r	MAE	MSE	r	MAE	MSE	r	MAE
LR-0-B-L (Linear Regression)	6.14E-05	0.225179	0.006062	0.000128	-0.04068	0.00934	0.000162	0.032731	0.009185
MLP-1-B-L (Multilayer Perceptron)	6.63E-05	0.385988	0.006277	9.75E-05	0.387156	0.00758	0.000189	0.246195	0.010786
PNN-0-N-N (Probabilistic Neural Network)	6.33E-05	0.264717	0.006197	0.000124	-0.10241	0.009129	0.000152	0.407749	0.008731
RBF-1-B-L (Radial Basis Function)	5.67E-05	0.35439	0.005712	0.000121	0.086661	0.008966	0.000153	0.264472	0.008953
GFF-1-B-L (Generalized Feedforward)	5.34E-05	0.429815	0.005569	0.000114	0.220347	0.008964	0.000137	0.434514	0.009379
MLPPCA-1-B-L (MLP with PCA)	0.0001	0.096097	0.008315	0.0001	0.354543	0.007841	0.000187	0.335483	0.011012
SVM-0-N-N (Classification SVM)	5.01E-05	0.713087	0.005509	0.000122	0.182953	0.009025	0.000158	1.92E-05	0.008771
TDNN-1-B-L (Time-Delay Network)	5.51E-05	0.422241	0.005694	0.000108	0.311372	0.008222	0.000175	0.134919	0.010114
TLRN-1-B-L (Time-Lag Recurrent Network)	0.000109	0.297027	0.008815	0.000127	0.192486	0.008218	0.000249	0.021465	0.012578
RN-1-B-L (Recurrent Network)	7.43E-05	0.025702	0.006659	0.000129	0.152358	0.009565	0.000151	0.203942	0.0088
MLP-2-B-L (Multilayer Perceptron)	8.9E-05	0.281612	0.007785	0.000107	0.257832	0.008078	0.000198	0.371451	0.011612

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Table A7 – The monthly combined model 1986-29010

Performance Metrics

Model Name	Training MSE	Training r	Training MAE	Cross Validation MSE	Cross Validation r	Cross Validation MAE	Testing MSE	Testing r	Testing MAE
LR-0-B-L (Linear Regression)	0.000881	0.436464	0.0211	0.00249	0.1728044	0.038452942	0.005081	-0.15675	0.044487
MLP-1-B-L (Multilayer Perceptron)	0.001204	0.419943	0.026369	0.002232	0.3518243	0.037509075	0.002161	0.368001	0.036218
PNN-0-N-N (Probabilistic Neural Network)	0.000983	0.532194	0.022573	0.002058	0.2539734	0.035616682	0.002717	-0.41387	0.03122
RBF-1-B-L (Radial Basis Function)	0.000912	0.403294	0.021167	0.002049	0.2648075	0.03528278	0.001529	0.592965	0.028292
GFF-1-B-L (Generalized Feedforward)	0.000614	0.681629	0.018283	0.003465	0.4037179	0.04756625	0.004992	0.197406	0.044756
MLPPCA-1-B-L (MLP with PCA)	0.001149	0.166821	0.025228	0.00185	0.3691626	0.034288595	0.00355	-0.17383	0.041165
SVM-0-N-N (Classification SVM)	0.004074	0.424642	0.056874	0.003751	-0.118476	0.048756521	0.003796	0.185073	0.049398
TDNN-1-B-L (Time-Delay Network)	0.001665	-0.11328	0.03152	0.002131	0.3265335	0.036308594	0.003183	-0.10084	0.040849
TLRN-1-B-L (Time-Lag Recurrent Network)	0.001551	-0.0764	0.029157	0.002041	0.0198916	0.034493003	0.002602	0.066341	0.035629
RN-1-B-L (Recurrent Network)	0.001158	0.331843	0.026865	0.002496	-0.006904	0.039600207	0.004098	-0.24651	0.042039
MLP-2-B-L (Multilayer Perceptron)	0.000982	0.407435	0.022127	0.001988	0.2169589	0.034850197	0.002098	-0.05299	0.032204

Table A8 – The monthly combined model in cycle period 1995-2010

Performance Metrics

Model Name	Training MSE	Training r	Training MAE	Cross Validation MSE	Cross Validation r	Cross Validation MAE	Testing MSE	Testing r	Testing MAE
LR-0-B-L (Linear Regression)	0.001039	0.545213	0.025309	0.000514	0.597673	0.016031	0.001508	0.687595	0.027999
MLP-1-B-L (Multilayer Perceptron)	0.001036	0.562722	0.024731	0.000328	0.617565	0.012943	0.00199	0.580225	0.031109
PNN-0-N-N (Probabilistic Neural Network)	0.001277	0.644972	0.027337	0.00046	0.542356	0.016901	0.002447	0.520829	0.034794
RBF-1-B-L (Radial Basis Function)	0.001018	0.557835	0.025086	0.0005	0.519866	0.015191	0.002609	0.347776	0.036924
GFF-1-B-L (Generalized Feedforward)	0.001029	0.560506	0.025243	0.00042	0.609561	0.014836	0.002083	0.574041	0.032573
MLPPCA-1-B-L (MLP with PCA)	0.001157	0.47057	0.026926	0.000426	0.564319	0.014899	0.002199	0.517187	0.032704
SVM-0-N-N (Classification SVM)	0.002372	0.486543	0.039203	0.001736	0.447124	0.038164	0.003325	0.268913	0.041291
TDNN-1-B-L (Time-Delay Network)	0.000695	0.741473	0.019252	0.000604	0.37252	0.018325	0.002792	0.283954	0.036644
TLRN-1-B-L (Time-Lag Recurrent Network)	0.000512	0.814481	0.01652	0.000487	0.424129	0.016335	0.006545	0.001909	0.060527
RN-1-B-L (Recurrent Network)	0.001491	0.472884	0.02792	0.000924	0.500015	0.023757	0.004985	0.3843	0.054115
MLP-2-B-L (Multilayer Perceptron)	0.00138	0.257846	0.029695	0.000381	0.549352	0.01528	0.002959	0.132089	0.037133

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