Advances in Behavioral Finance & Economics: The Journal of the Academy of Behavioral Finance Volume 1, Issue 1, Winter 2011 1-26

ISSN: 1551-9570

Investor Behavior and Economic Cycles: The Impact of Human Biases and Cognitive Limitations on Economic Booms and Busts

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Abstract

In light of the current great recession, this paper examines whether investor behavior and biases in information processing had contributed to the severity of economic cycles and how these human factors were revealed across time taking into account regulatory, technology, and market changes. We explore the impact of market participants' behavior on the economic cycles under various market conditions using time series/panel data and investigate (i) whether human behavior exacerbated the baseline dynamics of economic cycles across time (ii) what and how behavioral characteristics contribute to a cycle when market rules and conditions change and (iii) policy implications for sustainable growths in an economy.

Keywords: behavioral finance; behavioral economics; economic cycles; investor behavior; human nature; emotion; cognitive limitation; neuroeconomics; financial crisis; market sentiment

JEL Codes: A3; E3; G3

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1. Introduction

Since the industrial revolution in the late 18th century, the occurrence of economic cycles has been an inborn phenomenon 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 economic cycles occurred in the US and other OECD countries in the recent past had generated short- and long-run costs that severely impacted lives around the globe.

During an economic expansion, assets are overvalued while consumption goes overboard. Incomes are redistributed or reallocated to a small percentage of a population, a scenario that further exacerbates inequality and is the root cause contributing to the current crisis (Raghuram, 2005). In a recessionary economy, such as the one we just experience, millions lost homes, jobs, life savings, and are deprived of aspiring educational as well as professional experiences. The quality of life for millions of Americans had been sabotaged and the estimated damages in dollar terms are $8.3 trillion in savings and investments, pensions, home equities, and retirement assets. At the aggregate level, U.S. population 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. After the WWI and before the 1929 Great Depression, stock prices had steep appreciations as a result of excessive, highly leveraged, and speculative investments in the equities. The market crash came after the declines of real estate values. In more recent decades, the surges of stock prices during the boom time were triggered by new or innovative development in specific industries or product, e.g., the dotcom bubble in the 1990s and the subprime mortgage backed securities started in the mid-1900s. This is shown by the technology heavy Nasdaq Index (Figure 2A) and a comparison of stock prices between the Bank of America Corporation and a real estate equity value index (Figure 2F), as an illustration of the financial industry boom and crash originated in the real estate related investing.

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 led to biases reflexive of the dynamics and complex market externalities, may fill the void. In addition, given that the magnitude of the stock prices had noticeably 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.

In view of the impact of changes in financial regulations on the market structure in the past decade, this paper takes the opportunity to explain how these changes have created conflicts of beliefs in economic terms that short-circuited the 2008 crisis (Chang, 2008). Moreover, development and expansions in financial products as a result of deregulation had debilitated investors' cognitive understanding of the market mechanisms due to complex yet structurally unsound innovations, taking into account human nature and the social and incentive structures at the individual, corporate, and industry levels.

Given the destructive effects of stock market crashes, our research questions are:

I. How have markets evolved in terms of changes in technology, regulation, and financial innovations in the past decade? Is there a relation between these changes and changes in population disposition in the investment space in an economy?

II. What are the ramifications of changes in market rules and conditions in terms of influencing population behavior? Has market participants' behavior 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. How did human behavioral characteristics contribute to a cycle when market rules and conditions change? What are the unrealized consequences of these changes in the implementation process due to differed motivational dynamics and structures of human behavior between finance and the overall economic interest?

IV. Given the fundamentals of human nature and cognitive limitations in a dynamic and complex global market that led to structured biases or idiosyncratic deviations from technical fundamentals at the individual/industry level, what model could reflect the combined forces more accurately for better policies and for sustainable growths in an economy?

The significance of the paper includes (1) better explanation and control of financial performance and the development of empirical-based financial models with more weights on behavioral fundamentals for efficient management of capital (2) the development of new theories in finance and economics to bridge gaps between theory and the reality (3) reconciliation of different objectives between finance and economics with an optimization approach (4) better policy and educational apparatus given human characteristics for the well-being of an economy.

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

While the EMH along with the Rational Expectations Theory (RET) has 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 the busts.*

Proof: From Figure 1, we observe 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. In the case of the Great Depression in the 1920s, the average price to earnings ratio (P/E) of the S&P Composite stocks was 32.6. The rising share prices encouraged more people to invest, a symptom of heuristics (availability, representativeness, 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, employment, money supply, and ultimately the great depression.

Proposition 2: *A specific innovation or industry development had driven the trend.*

Proof: Figures 2A and 2C 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

[1] Limitations of arbitrage refer to the limits of correction forces or arbitraging away the difference between the market price and what the fundamentals dictate due to various restrictions.

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, magical thinking and cognitive limitations in understanding the nature of these products due to information asymmetry and other market externalities had led market participants to another bubble (see Figure 2D). As an example, the number of homes bought for investment jumped 50 percent during the four year period ending in 2004.

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

Proof: 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 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 allowed freedom for various financial innovations leading to the current crisis as a response.

Clearly, there was a misunderstanding or unawareness of the ramifications and market mechanisms that led to the calamity. The origination of the securitization of risky mortgages was intended to expand homeownership for a larger population on the one end and to offer higher rates of return on the other. However, from years of lending experience to the subprime borrowers in the unsecured credit market, retail lenders were well aware that subprime population would default at predictable levels. These characteristics were foreseeable elements for lenders to anticipate that investors would retreat investments when defaults occurred, a scenario that would trigger systemic and liquidity fallouts in a free market structure. However, lenders' knowledge of subprime borrower's characteristics was lost when loan portfolios were repackaged and transformed to investment houses.

Thus, the nature of the 2008 financial failure was the clash of conflicts or impenetrable forces of contradictions between the investors' belief in a capital market system and a popular idea of massive homeownership for unqualified borrowers – it was the fear of loss or losing control that had prompted investors to abandon investments that initially caused liquidity failure and eventually the system collapse. 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 from numerous excesses resulting from changes in regulations and policies, early enough to prevent a great recession.

Proposition 4: *The psychological tipping point led to the crashes.*

Proof: In the boom time, stock values were overvalued with P/E ratios well into double digits. Yet some might argue that not all bubbles burst. During the 1960-72 periods, P/E ratios were high for stocks but no crash occurred. In the cases of more recent crashes, the causes were due to investor skepticism in the market given various signals, i.e., household debt had reached to 98% of GDP and a substantial increase in the securitized loans and credits in the past decade (see Figures 4 and 5); while the subprime population had a long history of defaults. These mistrusts, which altered investor confidence level or risk perception, had caused fears and the need for a sense of control that led to the crashes.

During almost all boom and crash cycles, the fact that asset prices went from overvaluation to undervaluation without stopping at fair value made human psychology as a causal factor a case in point. This is because human decisions were made based on both rational and emotional factors or from reasoning and perception/intuition (Kahneman, 2002). The over-and 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 (Kent and Hirshleifer, 1998), played important roles in contributing to the economic shocks beyond the EMH. Figure 3 illustrates the mental process in a boom and bust scenario in the 2008 crisis.

3. Characteristics of Cognitive Limitations as Drivers of Asset Prices – A Neurophysiologic Approach

Modern finance under the theories of EMH presumes mean-variance measures in predicting and explaining decision making. However, the uncertainty in valuation in finance induces non-rational herding and produces non-mean-reverting dynamism. According to Evans (2006), mean and variance were among the weakest information cues on decision making relating to asset values.

Since human brains and emotions process information with particular comportments, it is essentially the operation of our psychological mechanics that determines the course of decision making. As people are both risk-avoiding and risk-loving; while many have strong urges to feel in control especially with tasks involving finance (Stotz and Nitzsch, 2005), some, such as the speculators, are keen on the excitement of gambling though with rational expectations of what the outcome might be. In the context of this study, we take the cases of those who are in need of the perception of control as well as those who seek to gamble, both of which result in cognitive and emotional limitations leading to biases, poor judgment, or so called 'irrational' behavior.

The following graph illustrates few salient characteristics or symptoms of cognitive limitations of the market participants in information processing and their interactions with behavioral outcomes that are considered to be drivers to the booms and busts of an economy.

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

A. *Mental Information Processing Mechanics and Behavioral Outcomes*

Characteristics that cause overconfidence associated with the perception of control are pay-off rationale/magical thinking, self-attribution, mental framing, and heuristics, which include representativeness, availability, and anchoring. Self-attribution occurs when one attributes successes to one's own judgment and failures to external factors and pay-off rationale/magical thinking is when one follows methods or uses factors that one believes had contributed to previous successes. While both of these mental mechanisms ignore the importance of the impact of changing externalities and variations in a complex market with different mix of factors on the outcomes, they fall into prey of typical cognitive limitations due to brain incapacity to encompass and interconnect with all available market information.

Steul (2006) found that ambiguity and correlation of investment portfolio affect the extent of the framing effect, a mental propensity to organize information in separate mental compartments that leads to short-term actions or myopic behavior with no long-term visions. Biases or misjudgments are also products of mental framing when words or phrases are selected and packaged with the intention to influence over one's perception in order to encourage or discourage certain interpretations. According to Diacon and Hasseldine (2007), presenting past information in terms of fund values and percent yields significantly affects investment fund preference and perceptions of risk and return.

Anchoring is a mental characteristic that disproportionately weighs on the first, preferred, available, or the most recent information received. It is an extreme version of the heuristics and the main cause of the under- and over-reaction given the "stickiness" nature of the mental attribute. Anchoring could cause poor judgment/estimation when irrelevant information was used in evaluating unknown values in forecasts. Two other heuristics are representativeness, which overstresses certain factors according to known or typical characteristics, and availability, when judgments are affected by the ease of accessibility of information or convenience. The combinations of anchoring, representativeness, and availability could lead to serious biases and herding in wrong directions when market participants form judgments collectively. Thus, herding is a product of incomplete information, preference, and imperfect rationality (Hirshleifer and Teoh, 2003). Herding can lead prices of speculative assets to deviate from their intrinsic value for a long time - a path to an artificially induced or non-productivity based boom.

B. Over and Under-confidence/reaction

Overconfidence occurs when the individual believes s/he knows or has the ability more than s/he actually does/has while reality shows limited evidence supporting the belief. According to a study by Stotz and von Nitzsch, people know or have the ability of about 66%-80% of what they believe they do. In addition, and according to the same study, analyst's past above-average forecast contributes to lower quality of judgment afterward. This is because higher perception of control contributes to overconfidence. Since perception of control is a key factor of psychological comfort, pursuit of a sense of control satisfies this need of reassurance. Yet, overconfidence intensifies when perception of control increases. So during boom time, seemingly good performances, which were often nominal, led to overconfidence – a phenomenon that shades investors and analysts from reality. The same study also shows that perception of control or overconfidence spreads from one company to the sector, a situation of herding behavior. Overconfidence has been the major contributor to severe boom-crash crises.

Overconfidence observed in the market 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. According to Hvide (2002), the outcome of under-confidence is the result of information asymmetry and ambiguity, uncertain and adverse situations, or wide dispersions of opinions that were not observable among market participants. From Richard L. Peterson's study (2007), it shows that investors with recent losses tend to be more risk-avert and those have gained large sums would take more risks. Figure 4 shows that the Barron's Investor Confidence Index follows the year-to-year percentage change of the S&P 500 index closely while economic cycles were vividly revealed in the latter as indicated in Figure 1. Hence, the confidence level of market participants correlates with or is attributable to booms and crashes of an economy.

Modern technology also contributed to the co-existence of over- and under-confidence. Since more information is available with easier access, it increases the perception of control for many market participants. On the other hand, the development of human brain remains almost constant and there are limitations to which human brains are able to absorb, process, and digest information. In many ways, technology advancements had made some tasks more complex and put humans on a relatively more vulnerable position in terms of making reliable judgment and decisions. In Allen and Evans' finding (2005), it shows that when experimental subjects perform difficult tasks, greater level of overconfidence is revealed. Yet over-confidence leads to greater under-confidence and fear. The phenomenon is illustrated by the volatility or fear index, a measure of stock deviation from the market expectation or confidence shocks, which spiked in the current economic cycle and since the dotcom bust in the mid-1990s as shown in Figure 5.

C. On Emotions and Human Nature

There are many shared human characteristics outplayed in the market. Often times, it is the greed or fear that exacerbated the severity of economic cycles. To many, the classical rational models were not only too demanding for most people to attain results required in the model assumptions, but also had excluded human emotions, preferences, and other personal sentiments. Combining psychology and physiology, neuroscientists had concluded that humans utilize both the logical part (the prefrontal cortex) as well as the emotional side (the Anteria) of the brain during decision-making processes. While humans have limited cognitive reasoning due to lack of mental efforts, habits, and capacity and biased cognitive intuitions affected by accessibility, heuristics, and framing during a decision-making process, the rational model lost its effect and power in predicting and controlling the economy and the financial market because of its negligence to the very foundations and mechanics of how human minds, brains, and emotions interact for the majority of the population. In addition, many of these human factors become more perceptible because of shared characteristics of human nature and desires under certain conditions such as less stringent rules and regulations.

D. On Externalities

While the standard theory of choice includes individual preferences with extensionality[2] and information changes in addition to income and price changes, behavioral and neuroeconomics 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 shape his/her perceptions and values in addition to genetic determinants that ultimately affect his/her judgment and choice. 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 caused by information asymmetry or a diverse pool of market participants' subjective opinions that contribute to market complications and conflicts.

Figure 6 shows the interactions of how human behavior and external factors contribute to the booms and busts of economic cycles.

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[2] According to Kahneman (2002), extensionality assumes that preference is not affected by negligible variations in the description of outcomes.

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 EMH and the RET where the asset price P is defined as

$$P=P^*+\varepsilon \tag{1}$$

And

$$P^* = E(P) \tag{2}$$

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 artificial and 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 ultimately led to poor judgments and biased behaviors..

Other related models, such as the Capital Asset Pricing Model (CAPM) where

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

were based on narrow assumptions that disregard investor preferences while work in contradiction with EMH, e.g., assets with low beta give higher returns than expected.

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 (or recurrent/feedback) and ambiguous characteristics in the economy that determines the real capital asset pricing in the market. Given the interconnectedness of multiple agents in the complex market, we use 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. The output variable is the S&P 500 Index (see Figure 7).

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 market participants 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 is a logistic function or sigmoid. In this case, 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 Figure 7 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 utilizes a feedback loop or recurrent 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 "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). There are also 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
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 on decision making. The process sums up the weighted inputs and determines 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 factors resulting from 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 weights on and the changes in the input variables as a response to the connections between the input and the hidden variables. Subsequently, the behavior of the output, the asset price in this 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 difference of the natural log from the previous period was used for modeling.[3]

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. Total consumer credit outstanding, which includes all consumer debts and loans secured and unsecured, were used to reflect deregulation since the late 1970s and the elimination of the Glass Steagall Act in 1999.

Since the mental mechanisms of market participants discussed in previous sections could only be observed through actions in buying or selling of assets reflected in asset prices and to study the relationship between the investor psychology and asset prices, behavioral variables associated with over/under-confidence and risk appetite that are reflexive of mental processes are used. These variables are representative of the investor mental state in terms of fear or need for control and their level of confidence and risk perceptions on the market; whether these perceptions were correct or not. Three sentiment indices, the Barron's Confidence Index (BCI)[4], the Volatility Index (VIX)[5], and the Consumer Confidence Index (CCI) from the University of Michigan represent the characteristics of the human psychology and the cognitive limitations of market participants outlined in previous sections. These variables were tested under the hidden layer in a multilayer-perceptron-architecture[6] of the neural network model to determine whether and to what extent they contribute to the variations of the output variable.

Panel data were used to investigate the impact of the variables selected before and after the effect of the booms and busts periods and to 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 and the post deregulation period from 1986-2010 when the sentiment related indices became available. Data were also divided between post- and prior- recession periods to gauge the significance of the

[3] 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.

[4] Barron's Confidence Index is the ratio of the average yield of top 10 high-grade bonds and the average yield of top 10 intermediate-grade bond indicating investors demand in returns given perceived risk level.

[5] Volatility Index is also an indicator of level of fears and has a negative relation with the S&P 500 in general.

[6] A 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.

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 data were used.

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

6. Model Results and Interpretations

Models were run and categorized in three types (1) models of behavioral fundamentals were regressed with sentiment variables only (2) models of technical fundamentals use technical measures such as dividend and earnings per share and (3) combined models apply variables of both types above in investigating the impact of these variables on the asset price. Tables 1-8 summarize the results.

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 framework. The fundamental model gave poor projection as shown in Table 3 due to low price correlation with fundamental variables. Nonetheless, the fundamental model improved during cycle years due to increased correlation with the earnings variable (see Table 4 and 10). The combined models give better results than those using fundamental variables only because of the addition of sentiment factors.

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[7]. See tables 9-13 for correlation and sensitivity analysis.

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 in Figure 8, which is another market sentiment variable, showed a striking increase prior to the 2008 crisis that further made the case in point.[8]

With limited sentiment variables available in this study, linear regression still gives optimal results in some cases in the model. However, we believe that neural network method is a superior approach in concept and is expected to provide richer results when more behavioral related variables become available with longer time frames. Future studies will strive to follow along these lines.

7. Concluding Remarks

This 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

[7] The first 144 data points span from 1990-2001 and the next 36 data points represent years of 2002-2004.

[8] 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.

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 2. Nonetheless, these extraordinary movements caused shifts 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 dominated the market in the past decades. Moreover, these human factors had intensified the effects of the expansions and the contractions in the economy driven by deregulation and other industry development in a free market system 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 injured the life qualities of the majority of the population 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 system interconnectedness while having limited modulations in the development of human nature, cognitive abilities, and emotions, the EMH and other modern financial theories had served more as ideological tools or what the market should be in normative economic terms 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 the past decades, cognitive biases will continue to exist due to imperfect human perceptions and its limited capacity to interact with complex externalities. And these imperfections were fundamental causes of economic booms and busts that had repeated 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.

Relating to market behavior during an economic cycle, investor responses to economic activities were pro-cyclical which intensified a boom or a bust condition. Taking these human behaviors and the law of effect into account, 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. In addition, the subprime lending, which triggered the current crisis, was a stimulus in defect in particular when borrowers were incapable of repay debts and investors were fearful 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 EMH presumes, should be encouraged through learning, distribution of quality information, and long-term investment objectives that contributes to the sustainability and real productivities of an economy. Policies that modulate to advance behavior consistent with the incumbent economic and political systems are expected to strengthen the efficiency of the market.

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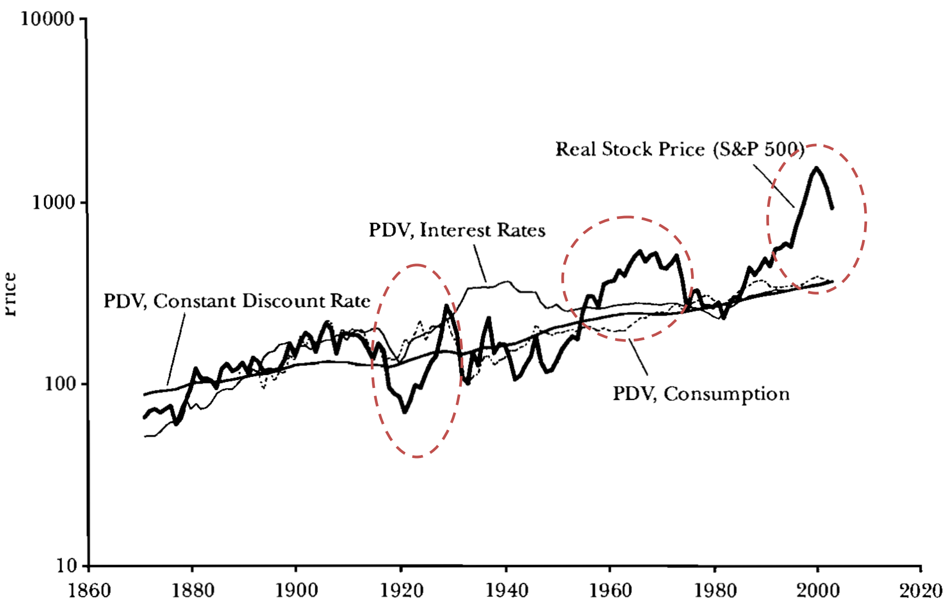
Figures

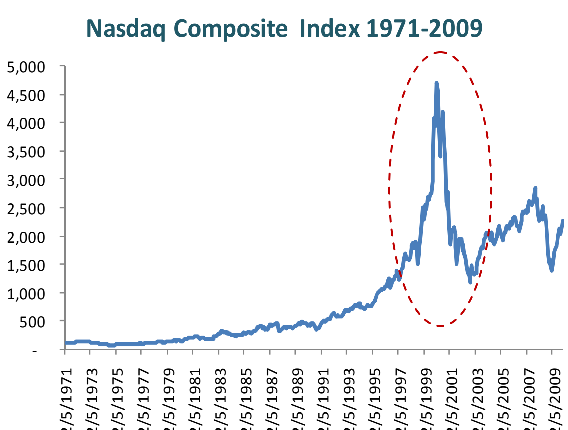
Figure 1



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.

Figure 2

Panel A



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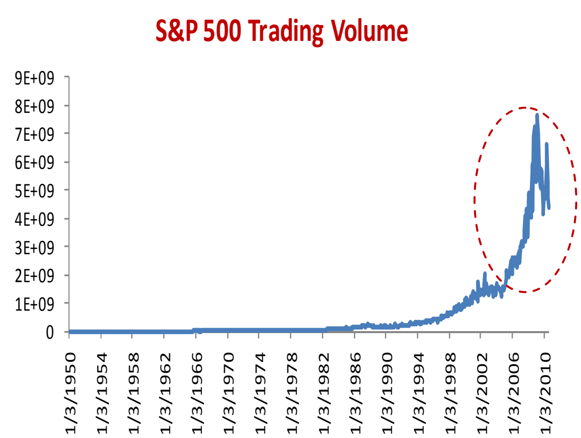

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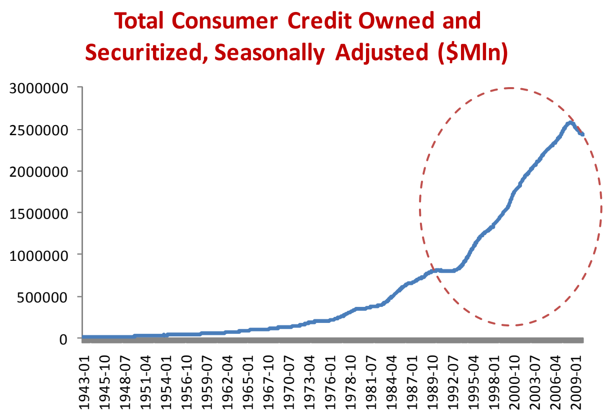

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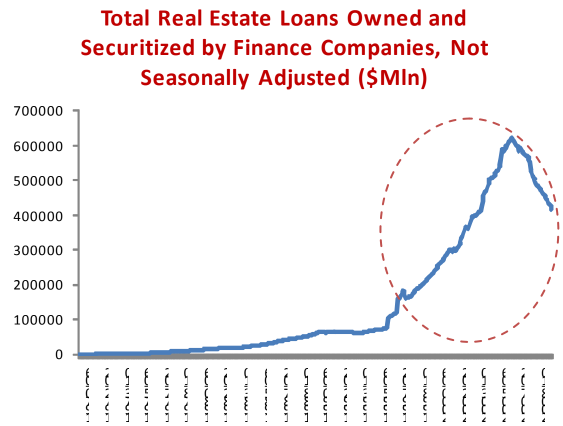

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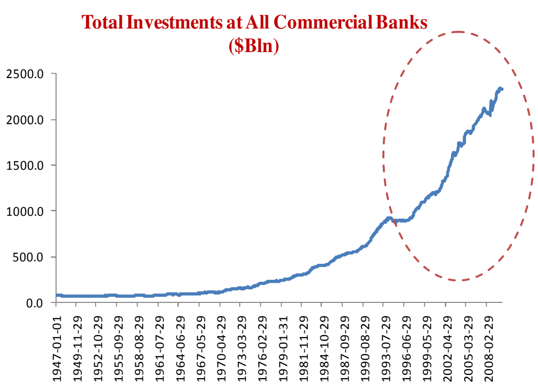

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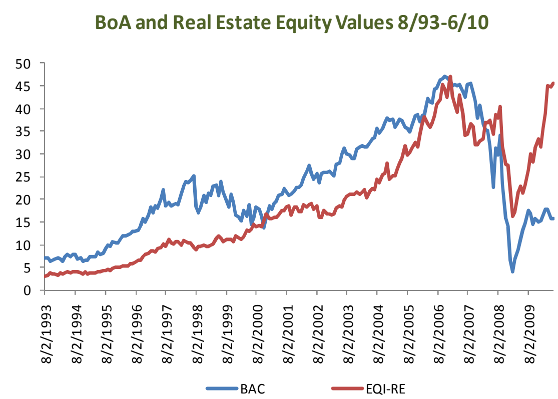

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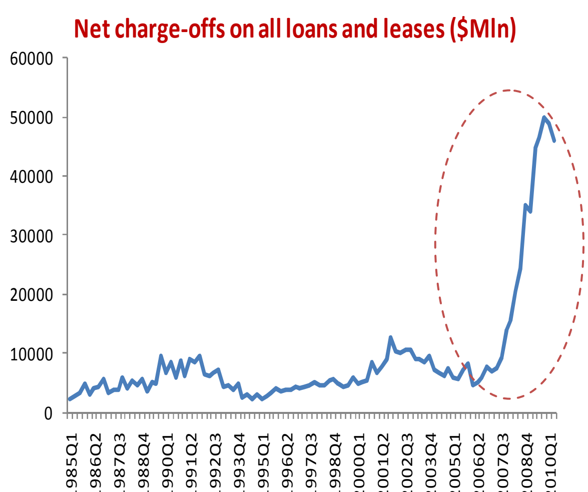

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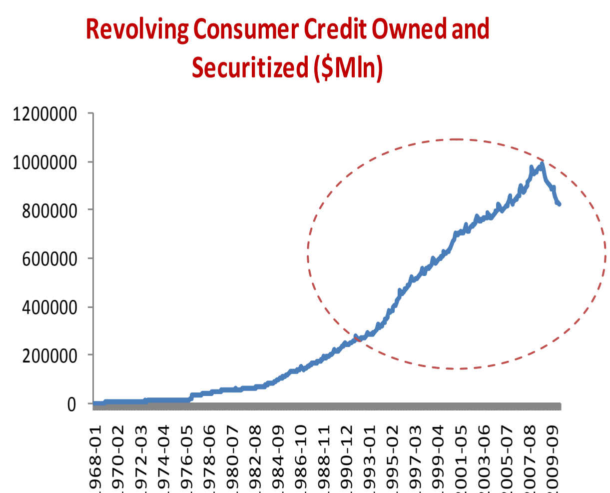


Source: Federal Reserve Bank of St. Louis

Figure 3

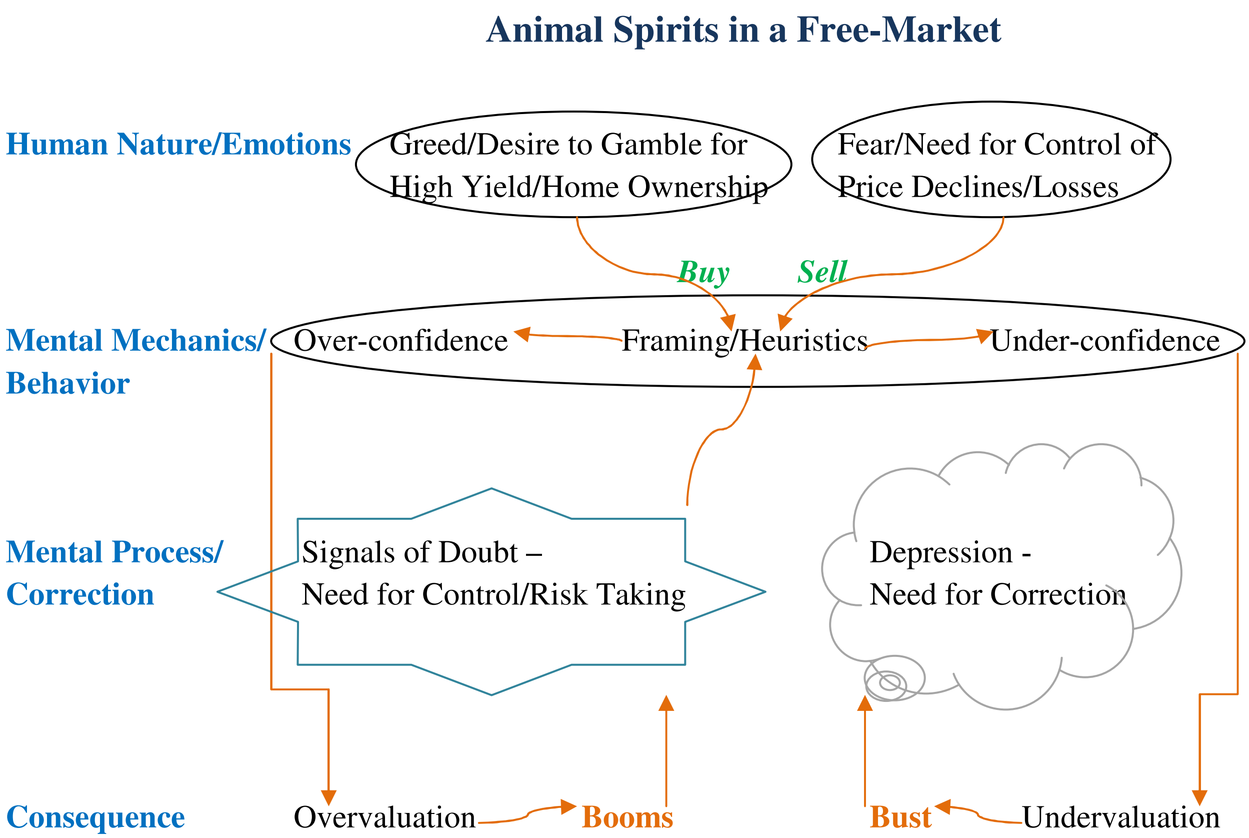
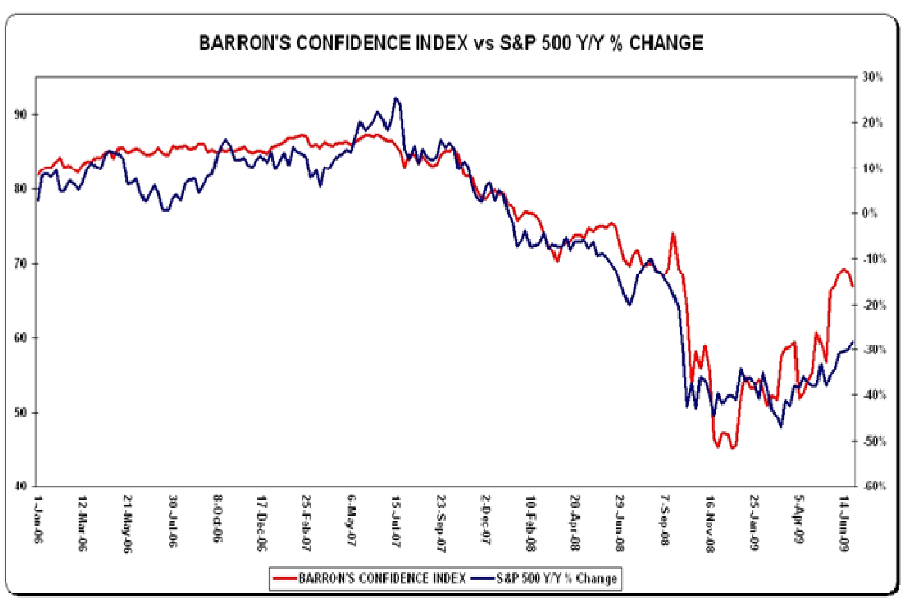
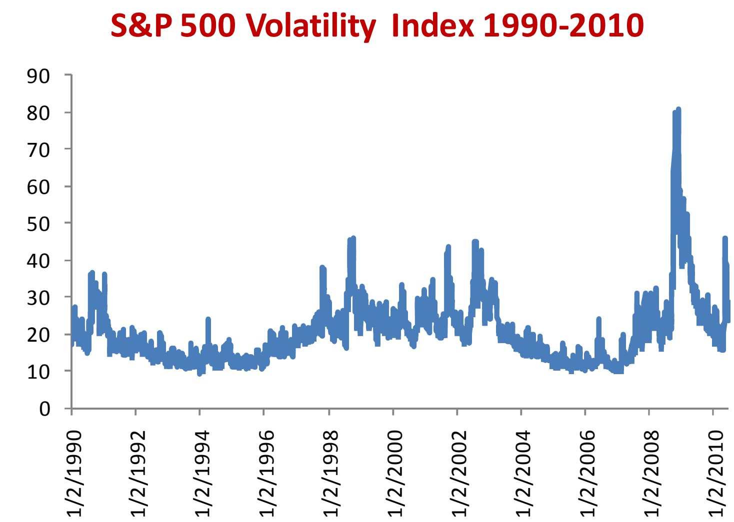


Figure 4



Source: Plexus Asset Management (based on data from I-Net Bridge)

Figure 5



Source: Yahoo! Finance

Figure 6

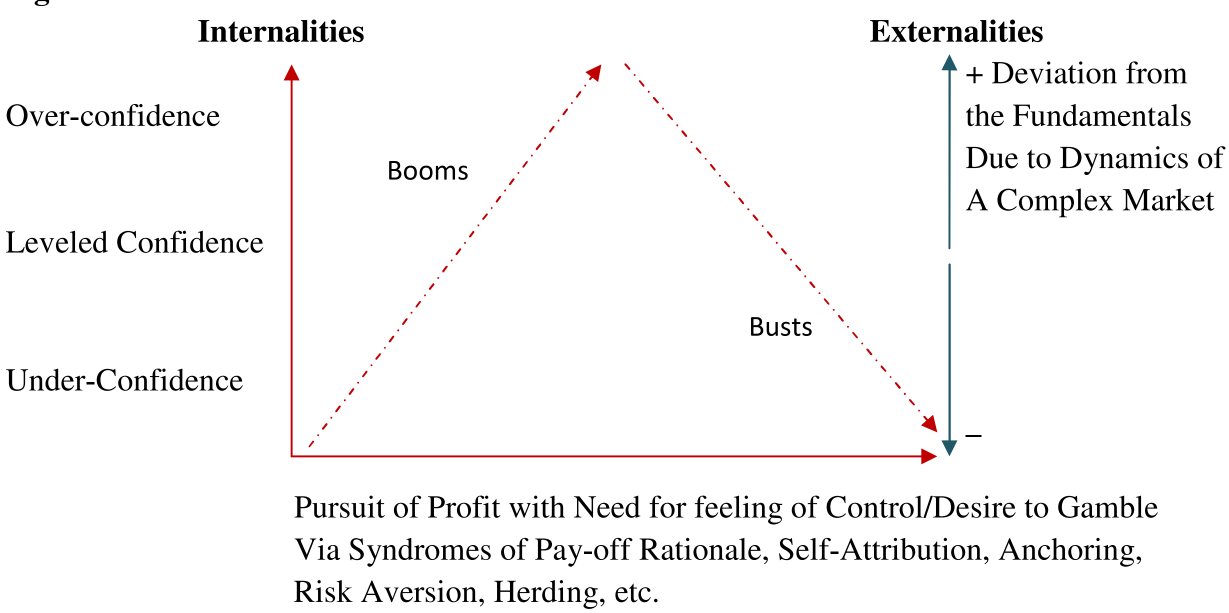


Figure 7

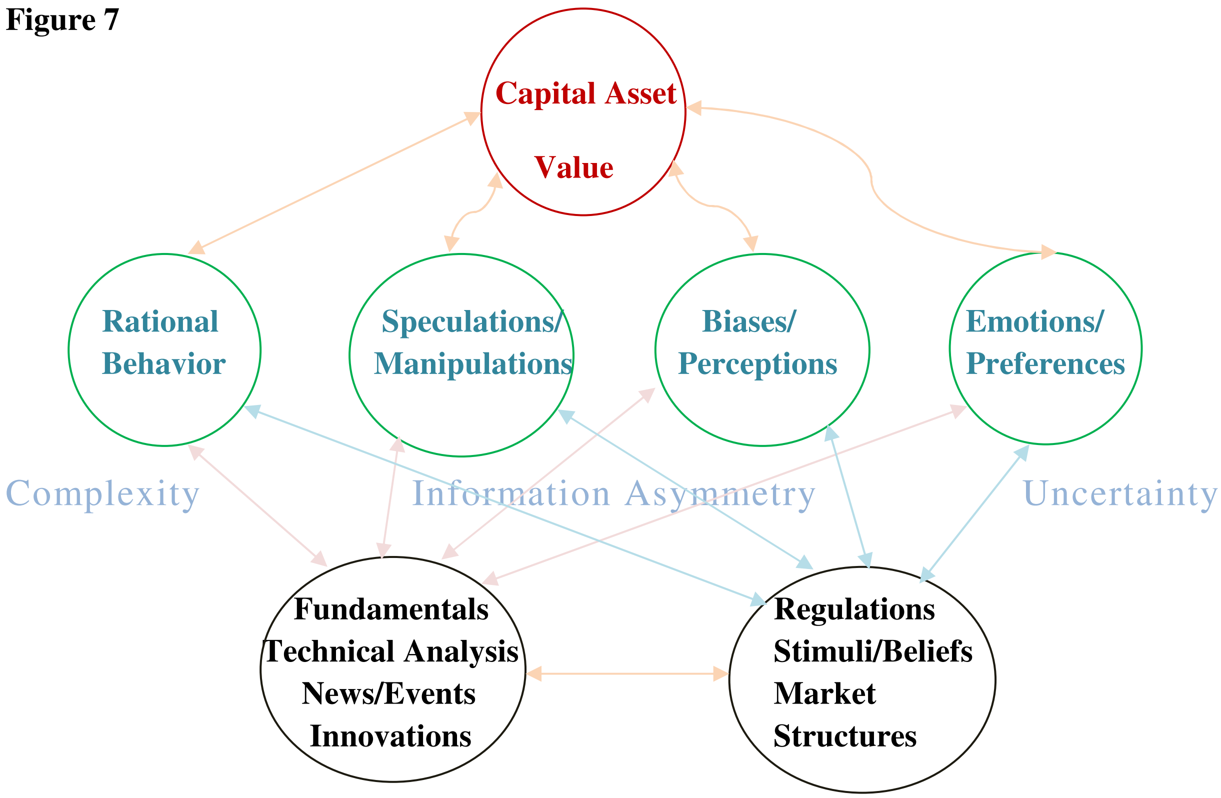
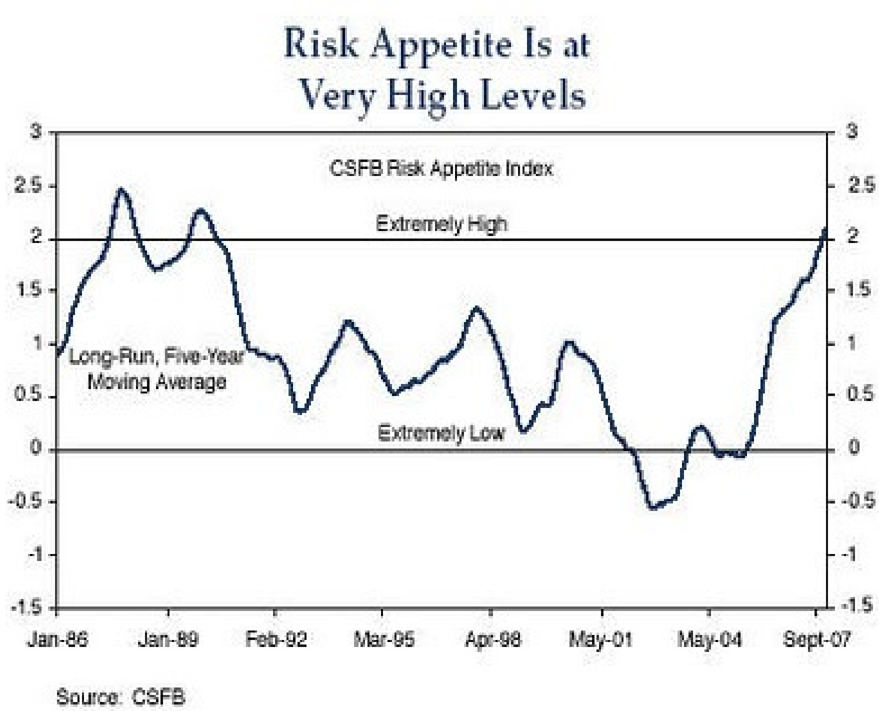


Figure 8



Tables

Models of Behavioral Fundamentals

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 Technical 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

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.

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

Appendix

Table A1

The weekly sentiment 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)	0.00025	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

	Training			Cross Validation			Testing		
Model Name	**MSE**	**r**	**MAE**	**MSE**	**r**	**MAE**	**MSE**	**r**	**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

	Training			Cross Validation			Testing		
Model Name	**MSE**	**r**	**MAE**	**MSE**	**r**	**MAE**	**MSE**	**r**	**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

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

Table A7 – The monthly combined model 1986-29010

Performance Metrics

	Training			Cross Validation			Testing		
Model Name	**MSE**	**r**	**MAE**	**MSE**	**r**	**MAE**	**MSE**	**r**	**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

	Training			Cross Validation			Testing		
Model Name	**MSE**	**r**	**MAE**	**MSE**	**r**	**MAE**	**MSE**	**r**	**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