Investor Psychology Perspective: a deep review on Behavioral finance

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Abstract

Determining the fair value of financial assets has been a controversial subject since the 1990s, and whether this value depends only on fundamentally calculated pricing models or if there are other psychological factors that affects it. The field of behavioral finance addressed these issues and provided some asset pricing models that incorporate behavioral aspects of decision-making and explained the different heuristics and biases behind these market reactions that lacked fundamental explanation. Behavioral finance is a relatively new paradigm that emerged to try to fill in the gaps in "Modern Finance". Behavioral finance models did not develop specific strategies to beat the market, however, it has highlighted lots of argumentative ideas that have promising directions of further research and analysis that may be very useful in public policy and welfare analysis, as well as in wealth management. In this paper, the author is presenting some of these behavioral finance theories and how they tackle the psychological aspects in investors' rational and irrational investment decisions.

Keywords: Behavioral Finance Financial Assets, Investor Psychology

1. Introduction

The Efficient Markets Hypothesis dominated the center stage of Finance Theory in the 1970's. Anomalous evidence that could not be fully accounted for by this hypothesis started showing up in 1980's in the literature. During the same period, advancements had been made in psychological theories, questioning the behavior of rational economic agents, but without necessarily applying them to investor behavior in financial markets. This, however, led to some literature attempting to explain anomalous evidence from a psychological viewpoint, but not in a formal way. In the 1990's, the development of financial economic models inspired by the psychology literature on behavioral biases and heuristics introduced the Behavioral Finance approach to the analysis of financial markets. In fact, the decade witnessed the development of a large body of behavioral finance literature. Looking into stock market crash in 1987, the internet bubble in 2000 and the financial crisis in 2008-2009, it is worth questioning the prices of these financial assets and whether value is the same thing as price. On the one hand, we could assume that these assets have a fundamental value that can be derived through various models and techniques of valuations based on the expected future cash flow, and that this value determines the asset prices. On the other hand, we could simply assume that the value of an asset is nothing but the price at which it can be sold at any given point in time. The field of behavioral finance addressed these issues and provided alternative asset pricing models incorporating behavioral aspects of decision-making and explained the different heuristics and biases behind these market reactions that lacked any fundamental explanation.
Behavioral finance is a relatively new paradigm that emerged to fill in the gaps in "Modern Finance". This gap reflects the failure of modern finance in which behavior was assumed to be derived by standard rational behavior rather than the psychologically impacted error-prone human behavior.
[7] pointed out that modern finance is built on the ground of rational behavior, and rests on four main building blocks, firstly, the "Mean- variance Portfolio Theory" of Markowitz [10], the "Arbitrage Process" developed through the "Dividends Irrelevance proposition" of Miller and Modigliani [13], thirdly, the CAPM developed through the work

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of Sharpe [12] and Lintner [14], and finally, the "Efficient markets Hypothesis" of Fama [3]. [7] pointed out that these gaps or soft spots are related to the very basic building blocks of modern finance.
The proposed model incorporates behavioral factors that complement the CAPM fundamental approach and develops a behavioral-based investment strategy driven by a set of variables derived from the literature on psychology and decision-making biases. This approach builds on the foundational idea proposed by Sharabi [1], who examined volatility expectations in financial markets from a behavioral perspective and highlighted the role of investor psychology in shaping market dynamics. The idea behind the model assumes that any stock's return at any given point in time cannot be fully explained by the extent of its systematic risk or beta. Accordingly, proxy variables for momentum effect and hindsight biases are selected and tested. The proposed variables are as follows:

- Stock Volume
- Stock Volatility Index
- Market Volume
- Market Volatility Index

Addressing the return contribution of such factors adds a new dimension of understanding for the sources of returns and points to a potential development of fundamental-based active portfolio management strategies.

2. Goal of the Study

Determining the fair value of financial assets has been a controversial subject since the 1990s, and whether this value depends only on fundamentally calculated pricing models or if there are other psychological factors that affect it. The field of behavioral finance addressed these issues and provided some asset pricing models that incorporate behavioral aspects of decision-making and explained the different heuristics and biases behind these market reactions that lacked fundamental explanation. Behavioral finance is a relatively new paradigm that emerged to try to fill in the gaps in "Modern Finance". Hence, this study aims to show that investors' psychology, clarified in the behavioral finance field, is a very important aspect that needs to be taken into consideration while looking at assets' valuation and pricing models. This is to further enhance the quantitative perspective of investors while taking their investments decisions
Behavioral finance models did not develop specific strategies to beat the market; however, it has highlighted lots of argumentative ideas that have promising directions of further research and analysis that may be very useful in public policy and welfare analysis, as well as in wealth management.

In this paper, we are presenting some of these behavioral finance theories and how they tackle the psychological aspects in investors' rational and irrational investment decisions. The paper's main goal is to prove through quantitative measurements for few selected S&P500 stocks that behavioral regularities play a very important role in determining the value of these stocks over a four years period of time starting in 2011 through 2014. This will be achieved by using statistical techniques proving that there are other components that can be added to the CAPM equation i.e. stock's volatility index, stock's traded volume together with the overall volume of the index that the stock is listed in (S&P500) and the Chicago Board Options Exchange (CBOE) Market Volatility Index (VIX), a popular measure of the implied volatility of S&P 500 index options. This proposed modified equation is believed to have a positive impact on the financial model to have a better prediction for the stock's value and price.

3. Hypothesis Testing

This paper addressed the question of whether prices reflect fundamental values and whether deviations of prices from value could be explained solely by the efficient framework. Our review of the literature has shown that the Efficient Market Hypothesis (EMH) could not stand up to the empirical challenges to its semi-strong and strong market efficiency. Instead, we chose to explore the behavioral framework of analysis to market anomalies, adding a psychological dimension to finance.

In fact, the cognitive errors and emotional biases play a major role in the investment decision-making process, resulting in irrational price performance and persistent mispricing that could not be fully accounted for by the efficient framework. Thus, the behavioral finance literature addressed the questions of why reality differs so much from the idealized world that underlies the efficient market and the Capital Asset Pricing Model and whether it could enable us to outperform the market. So far, behavioral finance models do not seem to have developed specific strategies to beat the market. Nevertheless, the field has promising directions of further research and analysis that may be very useful in public policy and welfare analysis, as well in wealth management. For example, it may be worthwhile to develop new investment products geared towards behavioral investors and practically applying the behavioral portfolio theory

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in wealth management. Also, regulators might consider carrying out a cost-benefit analysis of the welfare gains and losses entailed in taxing and borrowing to assess the welfare impact of margin trading and capital gain taxation.

Hence, this paper is addressing the question of whether investors' behaviors can, by adding other variables to the CAPM equation, help us to better estimate the discount rate which will lead to a better estimation to stocks' values and prices and consequently, can make better investment decision to maximize investors' welfare.

Where:

- $\mathbf{R_s}$ is the stock's weekly return
- $\mathbf{R_f}$ is the 10 year US T-bond
- $\mathbf{r_m}$ is the S&P500 market return
- $\boldsymbol{\beta}$ is the measure of the stock's risk in relation to the market
- $\mathbf{X_1}$ is the S&P500 Volatility index (VIX)
- $\mathbf{X_2}$ is the S&P500 traded Volume
- $\mathbf{X_3}$ is the stock's volatility index
- $\mathbf{X_4}$ is the stock's traded volume
- $\boldsymbol{\alpha}$ is the coefficient of volatility index
- $\boldsymbol{\Phi}$ is the coefficient of S&P500 traded volume
- $\boldsymbol{\eta}$ is the coefficient of stock's volatility index
- $\boldsymbol{\mu}$ is the coefficient of the stock's traded volume

4. The Behavioral Portfolio Theory

In contrast to the mean- variance portfolio theory, empirical evidence does not support that investor hold well diversified efficient portfolios.

Merton [8] provides a static asset pricing model with incomplete information. The key behavioral assumption of his model is that an investor only uses a certain security to form his optimal portfolio if he knows about this certain security. If all investors' information sets were complete, then the model would reduce to the standard Sharpe-Lintner CAPM. Such nonparticipation can be viewed as reflecting limited attention or preference for the familiar. In other words, he introduces such fractions as information costs and institutional structures in his model.

He concludes that the incomplete diffusion of information among investors has an empirically significant impact on equilibrium expected returns and especially so, for smaller firms with little institutional following. However, he states that in the long run the efficient market equilibrium should be reached again. It seems clear from the structure of the model and its emphasis on the information assumption that

Merton is defending the efficient market hypothesis by means of the Behaviouralists' arguments, namely by introducing incomplete information in the CAPM

[2] found out when studying the U.S stocks; a clear tendency for correlations among individual stocks to decline over time. Correlations over five years of monthly data declined from 0.28 in the early 1960s to 0.08 in 1997.

[7] pointed out that the current optimal diversification level, as prescribed by mean- variance optimizations should exceed 300 stocks, because at this level of diversification the benefits exceed the costs. Yet, Goetzmann and Kumar [4]; in a study of more than 40,000 stock accounts at a brokerage firm found out that the mean number of stocks in a portfolio in the 1991-1996 period was 4 and the median number is 3.

In the same vein, Polkovnichenko [5] found also in a survey of 14 million households in 1998 that they were holding portfolios of 1 to 5 stocks. What is more, there is evidence that supports the concentration of portfolios in particular styles, such as large capitalization stock, or locations whether regional or national.

Shefrin and Statman [6] developed behavioral portfolio theory as an alternative to the descriptive version of the Markowitz mean–variance portfolio. Mean–variance investors evaluate portfolios as a whole; they consider co-variances between assets as they construct their portfolios. Mean– variance investors also have consistent attitudes toward risk; they are always averse to risk.

Shefrin and Statman explain how BPT is consistent with the apparently irrational behavioral tendency of many people to purchase insurance policies and buy lottery tickets. A BPT investor maximizes expected wealth subject to the constraint that the probability of wealth being less than some aspirational level cannot exceed some specific probability. The investor can tolerate failure to achieve at least the aspirational level of wealth but only with a small probability. In other words, the investor maximizes expected wealth on a particular portfolio subject to safety constraint.

This phenomenon was clearly addressed in the Security, Potential and Aspiration (SPA) Theory by Lopes [11], it emphasizes that the decision maker when choosing among risky investment aims at maximizing security, potential and aspiration, yet in some situations the investor is willing to trade off some security and potential in exchange for high aspiration value.

The decision maker who experiences greater fear faces sharp reduction in security, where the investor with greater hope will have high probability of the occurrence of the favourable event. As a result, hope is tied to the upside potential and the degree to which hope, and fear are expressed in choices depends on the prospects offer of security and potential. Accordingly, Behavioral investors build portfolios as pyramids of assets, layer by layer. The layers are associated with goals and particular attitudes toward risk. Some money is in the downside-protection layer, designed to avoid poverty; other money is in the upside-potential layer, designed for a shot at being rich.

Simon [9] proposed the notion of bounded rationality, recognizing that people are not fully rational when making decisions and do not optimize but rather satisfice (satisfy and suffice) when arriving at a decision. Simon describes the phenomenon where people gather some not all available information, use heuristics to make the process of analyzing information and stop when they have arrived at a satisfactory decision and not necessarily the optimal one, that in contrast with the rational economic man making decisions according to the expected utility theory.

5. Theoretical Framework

5.1 Description of research design

This study is based on data from S&P500 index covering selected stocks' performances over a period of four years starting 2011 till 2014. The data used will include weekly prices for selected companies' stocks, together with their volatility indices and weekly traded volumes. The data obtained for different stocks in diversified sectors. To keep things simple, the data used is the closing price of each stock on the last trading day of the week. Also, for the sake of the study the volume and the volatility index of the S&P500 will be added to the model. The used risk-free rate in the model will be the US 10 years Treasury bond over the same specified period. Figure 1 and figure 2 show the CAPM modified equation to be tested and the Theoretical Framework Diagram, respectively.

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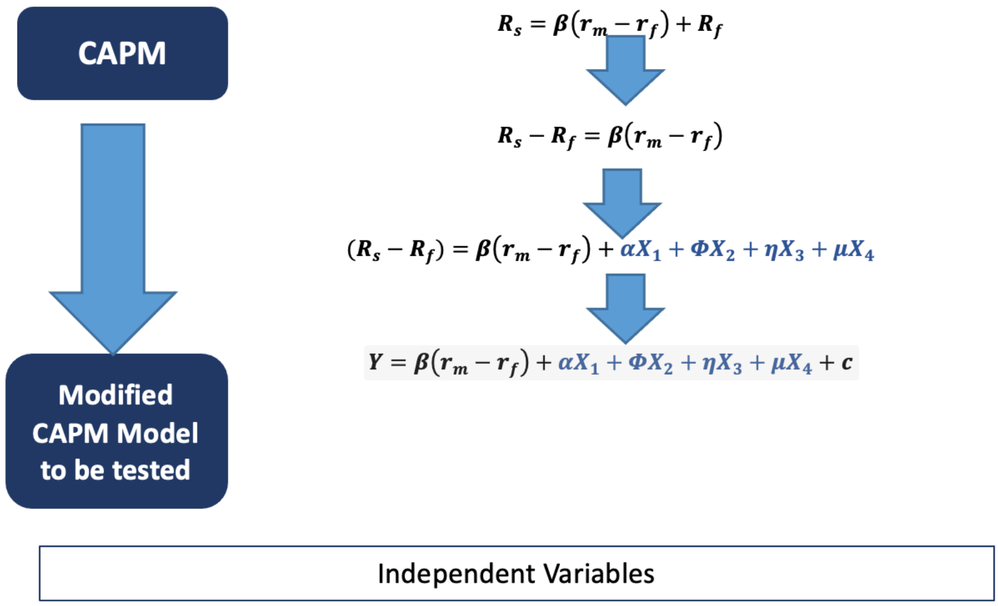

Figure 1: CAPM modified equation to be tested

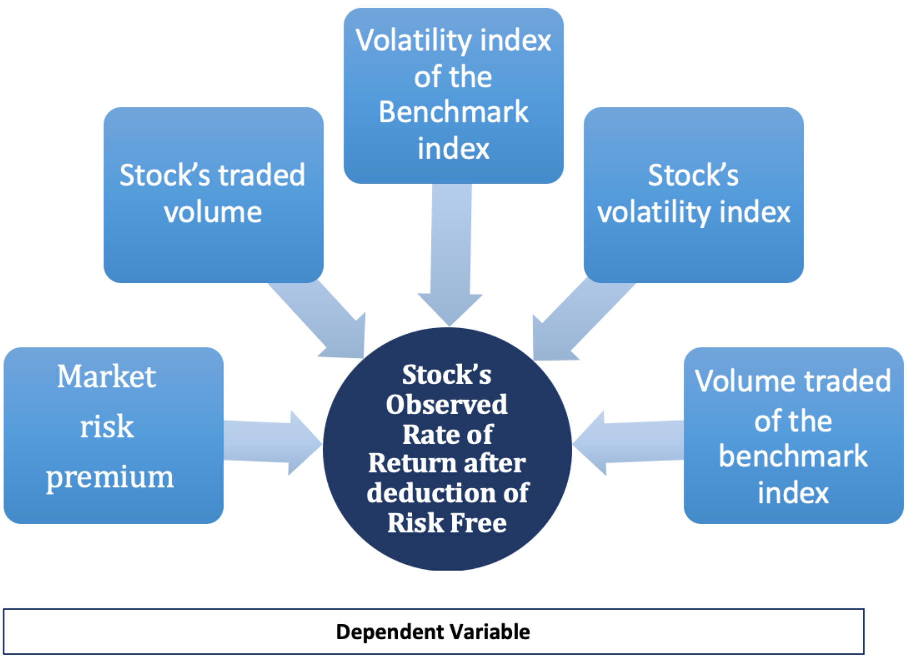

Figure 2: Theoretical Framework Diagram

5.2 Procedures & Data Processing
The preliminary suggested methodology entails gathering weekly close prices for selected stocks, as well as market indices for 4 years starting 2011 till 2014.

The data gathered will be used to run several multi-variable models regressing the return lags under different period assumptions, the volume changes, and the market returns on the actual selected stock returns.

The selected stocks are chosen based on the following criteria:

- Stocks are constituent of the S&P500 index with big market capitalization
- Stocks to be from different sectors to ensure generalization

- All stocks must have volatility index
- Selected stocks must have high liquidity with high daily traded volumes

The hypothesis will be tested by using the SPSS statistical model, to run a regression testing on the chosen data and check for the R^2. The R^2 is the coefficient of determination which is a statistical measure of how well the regression line approximates the real data points.

Using this criterion, the higher the R^2 the higher the correlation between our variables, showing higher probability that behavioral finance (translated into our 4 suggested variables i.e. x_1, x_2, x_3, x_4) can be used to further enhance the CAPM equation.

The study will base its hypothesis testing with confidence interval of 95%.

5.3 Data Analysis

The main aim of this paper is to prove that investors' behaviors have a noticeable effect on their investment decisions. Hence, I thought of modifying the CAPM famous equation that takes only into consideration two main variables in calculating required rate of return by investors on their alternative investments. Where the general idea behind CAPM is that investors need to be compensated in two ways: time value of money and risk.

$$\mathbf{R_s = \beta(r_m - r_f) + R_f}$$

Therefore, by adding certain variables that, in my opinion, are valid variables to be used as quantification to investors' behaviors qualitative variables, will enhance the CAPM equation by making it more indicative and reliable in estimating the required rate of return.

This study is based on data taken from the American stock exchange and specifically stocks listed on the S&P500. The choice of the S&P500 index is based on the fact that it is one of the most actively traded and reliable indices in the American stock market.

The criteria that stocks were chosen accordingly was as follows:

1- Different sectors
2- Listed on the S&P500
3- Have a volatility index

The chosen stocks were from different sectors; this is to show that behavioral finance can be applied on all and any sector. The selection of the stocks was also based on the fact that they have a volatility index since 2011, the Chicago Board Options Exchange (CBOE) is the world's largest options exchange & the leader in product innovation, options education, & trading volume. The CBOE calculates and updates the values of more than 25 indexes designed to measure the expected volatility of different securities. These volatility indexes are key measures of market expectations of near-term volatility conveyed by listed option prices. Futures and options contracts now are available on some of these volatility indexes. The CBOE Volatility Index (VIX) is the world's most widely followed barometer of investor sentiment and market volatility.

The model we are presenting is based on weekly data collected historically from January 2011 until December 2014.

As shown in Table 1 are the selected stocks with their volatility indices used:

Table 1: Selected Stocks for sake of study

Stock	Code	Volatility Index
Citi Group	C	CVOL
IBM	IBM	VXIBM
Google	GOOGL	VXGOG
Goldman Sachs	GS	VXGS

Amazon	AMZN	VXAZN
Apple	AAPL	VXAPL

The study was done on each stock separately where a regression analysis was conducted, to see how by adding extra meaningful variables to the CAPM equation investors can enhance their expected return from each stock.

$$\mathbf{R_s = \beta(r_m - r_f) + R_f}$$

This is the CAPM equation and for the sake of the study the $\mathbf{R_f}$ rate was moved to the left-hand side of the equation, making it the **Y** variable or the dependent variable in the new equation as follows;

$$\mathbf{(R_s - R_f) = \beta(r_m - r_f)}$$

As mentioned earlier, investors' behavioral actions concerning their investments will be quantified in this study in four main variables that are mentioned below:

1- The benchmark index's volatility index $\mathbf{X_1}$

2- The benchmark index's traded volume $\mathbf{X_2}$

3- Stock's volatility index $\mathbf{X_3}$

4- Stock's traded volume $\mathbf{X_4}$

Therefore, this is how the modified CAPM equation that will be tested in this study looks like;

$$\mathbf{Y = \beta(r_m - r_f) + \alpha X_1 + \Phi X_2 + \eta X_3 + \mu X_4 + c}$$

Where:

- $\mathbf{R_s}$ is the stock's weekly return
- $\mathbf{R_f}$ is the 10 year US T-bond
- $\mathbf{r_m}$ is the S&P500 market return
- $\boldsymbol{\beta}$ is the measure of the stock's risk in relation to the market
- $\mathbf{X_1}$ is the S&P500 Volatility index (VIX)
- $\mathbf{X_2}$ is the S&P500 traded Volume
- $\mathbf{X_3}$ is the stock's volatility index
- $\mathbf{X_4}$ is the stock's traded volume
- $\boldsymbol{\alpha}$ is the coefficient of volatility index
- $\boldsymbol{\Phi}$ is the coefficient of S&P500 traded volume
- $\boldsymbol{\eta}$ is the coefficient of stock's volatility index
- $\boldsymbol{\mu}$ is the coefficient of the stock's traded volume

Market Risk Premium: $\mathbf{(r_m - r_f)}$ this is the part in the CAPM that represents risk and calculates the amount of compensation the investor needs for taking on additional risk. This is calculated by taking a risk measure (beta) that compares the returns of the asset to the market over a period of time and to the market premium (Rm-rf). In other words, shows how much the investors are willing to take as extra risk over the expected market return.

The added variables are divided into two classes; one of them is directly related to the stock and its performance (stock's traded volume and stock's volatility index) and the other group is related to the index that this stock is listed it (the index traded volume and the index volatility index).

1- Investors always tend to trade in stocks that are listed in well-known and active indices like the S&P500 as they see that these stocks are trusted in the sense that they are included in such a big index which gives a sense of confidence in the stock regardless of the specific details of each stock on its own

2- Stock specific data: the data related to the stock itself; its volume and volatility index. After investors take the bigger picture, represented in the index, they start looking at each stock's specific data. This will give them a clearer picture about the company apart from its fundamentals. This ensures for investors a higher expected return

The first added variable in the modified equation is the **Stock's traded volume** $\mathbf{X_4}$. The stock's traded volume is a very important indicator to how investors observe the stock; the higher the volume the more confident investors are towards the stock.

This is because investors generally prefer to trade in liquid stocks. Consequently, higher trading volume signals broader investor confidence, attracting additional rational investors who view high-volume stocks as more trustworthy.

Stock's volatility index $\mathbf{X_3}$: For the sake of the study, the stocks were chosen based on the fact that they have a volatility index. This is considered a limitation to the study, as only six stocks were found that have a volatility index published by the CBOE. Stock's volatility index is a contrarian sentiment indicator that helps determine when there is too much optimism or fear in the market. When the sentiment reaches one extreme or the other, the market typically reverse course. That is why we believe that volatility index is a very good quantification method to investors' behavioral trends and attitudes as it shows how the stock driven by investors' actions is volatile over a specific period.

The two other factors that is related to the index that each stock is listed in. the first variable in this group is the **index's traded volume** $\mathbf{X_2}$. This variable shows how confident investors are in the index itself as some investors start their trading by picking the index and then seeing the stocks listed in it to decide whether to invest in them or not. The benchmark index's volume is the best indicator for such a thing as it shows how active an index is unlike turnover, which is affected by prices where volumes are, will give absolute figures of stocks.

The same logic applied to the stock's volatility index also applies to the **benchmark index's volatility index** $\mathbf{X_1}$as well where the volatility index will show how investors observe market trends and their variability over time.

Each stock's data is analyzed separately, regressing the independent behavioral variables against the dependent variable **Y**. The procedures taken in the regression will show the effect of adding extra variables to the CAPM equation and how this can give better estimation to investors' required rate of return after adjusting it to the risk-free rate.

Six stocks were chosen based on the above-mentioned criteria and their data were accessible and available for us to make use in the study.

We started by regressing market risk premium $(\mathbf{r_m - r_f})$ on our new variable **Y** which is the required rate of return subtracted from it the risk-free rate. As observed, the ANOVA table gave the following results for each stock.

1- Citi group (C)

Table 2: Citi Group ANOVA Table

2- Goldman Sachs (GS)

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.721284636
R Square	**0.520251526**
Adjusted R Square	0.517911289
Standard Error	0.033156374
Observations	207

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.244392384	0.244392384	222.3072474	1.5467E-34
Residual	205	0.225365747	0.001099345		
Total	206	0.469758131			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.0002909	0.002310389	-0.12590941	0.899927031	-0.004846072	0.004264272	-0.004846072	0.004264272
X Variable 1	0.779902145	0.052307421	14.90997141	1.5467E-34	0.676772652	0.883031638	0.676772652	0.883031638

Table 3: Goldman Sachs ANOVA Table

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.825588018
R Square	**0.681595576**
Adjusted R Square	0.680042384
Standard Error	0.026140813
Observations	207

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.299874625	0.299875	438.8353	7.64104E-53
Residual	205	0.140085134	0.000683		
Total	206	0.439959759			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.00082596	0.001821534	-0.45344	0.65071	-0.004417303	0.002765382	-0.004417303	0.002765382
X Variable 1	0.863905303	0.041239688	20.9484	7.64E-53	0.782596989	0.945213617	0.782596989	0.945213617

3- Google (GOOGL)

Table 4: Google ANOVA Table

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.878674164
R Square	**0.772068286**
Adjusted R Square	0.770956424
Standard Error	0.024590517
Observations	207

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.419894456	0.419894456	694.3921758	9.46403E-68
Residual	205	0.123962174	0.000604694		
Total	206	0.54385663			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.001681757	0.001713507	-0.981471124	0.327517348	-0.005060114	0.001696599	-0.005060114	0.001696599
X Variable 1	1.02227173	0.038793945	26.35132209	9.46403E-68	0.945785453	1.098758007	0.945785453	1.098758007

4- Apple (AAPL)

Table 5: Apple ANOVA Table

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.790662546
R Square	**0.625147261**
Adjusted R Square	0.623318711
Standard Error	0.034630536
Observations	207

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.410009502	0.410009502	341.8814247	1.46897E-45
Residual	205	0.245851169	0.001199274		
Total	206	0.655860672			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.002311895	0.002413111	0.958055683	0.339163199	-0.002445804	0.007069594	-0.002445804	0.007069594
X Variable 1	1.01016715	0.054633055	18.49003582	1.46897E-45	0.902452427	1.117881873	0.902452427	1.117881873

5- Amazon (AMZN)

Table 6: Amazon ANOVA Table

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.765342035
R Square	**0.58574843**
Adjusted R Square	0.583727691
Standard Error	0.037650958
Observations	207

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.41091585	0.41091585	289.8683718	4.26367E-41
Residual	205	0.290606901	0.001417595		
Total	206	0.701522751			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.002443013	0.0026184	0.933017715	0.351908418	-0.002719433	0.007605459	-0.002719433	0.007605459
X Variable 1	0.99292336	0.058319704	17.02552119	4.26367E-41	0.877940027	1.107906693	0.877940027	1.107906693

6- IBM (IBM)

Table 7: IBM ANOVA Table

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.882799449
R Square	**0.779334868**
Adjusted R Square	0.778258453
Standard Error	0.022188794
Observations	207

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.356460691	0.356460691	724.0094814	3.4024E-69
Residual	205	0.100930227	0.000492343		
Total	206	0.457390918			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-4.43506E-05	0.001543098	-0.028741241	0.977098925	-0.003086729	0.002998027	-0.003086729	0.002998027
X Variable 1	0.924794213	0.034369481	26.90742428	3.4024E-69	0.857031224	0.992557203	0.857031224	0.992557203

We focused on observing $\mathbf{R^2}$ and how it will change for each stock, by the addition of the new behavioral variables to the regression equation. We found that by adding the four variables the $\mathbf{R^2}$ was enhanced in all stocks tremendously as presented below.

1- Citi group (C)

Table 8: Citi Group modified ANOVA Table

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.794426058
R Square	**0.631112761**
Adjusted R Square	0.623808063
Standard Error	0.029289252
Observations	207

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	0.296470351	0.074117588	86.39820267	1.16801E-42
Residual	202	0.17328778	0.00085786		
Total	206	0.469758131			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.004864207	0.002209334	-2.201661911	0.028821377	-0.009220522	-0.000507892	-0.009220522	-0.000507892
X Variable 1	0.836929056	0.047497887	17.62034275	1.04615E-42	0.743273796	0.930584316	0.743273796	0.930584316
X Variable 2	-0.155695093	0.027025013	-5.761147827	3.08207E-08	-0.208982402	-0.102407784	-0.208982402	-0.102407784
X Variable 3	0.019275398	0.008132814	2.370077304	0.018726087	0.003239299	0.035311497	0.003239299	0.035311497
X Variable 4	0.050425775	0.025258115	1.996418798	0.047231147	0.000622396	0.100229155	0.000622396	0.100229155

2- Goldman Sachs (GS)

Table 9: Goldman Sachs modified ANOVA Table

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.844004824
R Square	**0.712344143**
Adjusted R Square	0.706647988
Standard Error	0.025030378
Observations	207

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	0.313402758	0.078350689	125.0570027	1.61883E-53
Residual	202	0.126557001	0.00062652		
Total	206	0.439959759			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.001067774	0.001756346	-0.607952276	0.543902037	-0.004530897	0.002395349	-0.004530897	0.002395349
X Variable 1	0.884407316	0.040617449	21.77407334	6.81728E-55	0.804318748	0.964495883	0.804318748	0.964495883
X Variable 2	-0.084823692	0.021055482	-4.028579929	7.94183E-05	-0.126340416	-0.043306969	-0.126340416	-0.043306969
X Variable 3	0.014606461	0.006967131	2.096481531	0.037284468	0.00086883	0.028344092	0.00086883	0.028344092
X Variable 4	0.031224565	0.017607305	1.773386994	0.077671375	-0.00349312	0.065942251	-0.00349312	0.065942251

3- Google (GOOGL)

Table 10: Google modified ANOVA Table

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.896577973
R Square	**0.803852062**
Adjusted R Square	0.799967944
Standard Error	0.022980443
Observations	207

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	0.437180273	0.109295068	206.9587348	2.92262E-70
Residual	202	0.106676357	0.000528101		
Total	206	0.54385663			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.00206514	0.001613094	-1.280235146	0.20193064	-0.005245803	0.001115523	-0.005245803	0.001115523
X Variable 1	0.974512154	0.037268524	26.14839707	9.26681E-67	0.901026922	1.047997386	0.901026922	1.047997386
X Variable 2	-0.029421221	0.014839842	-1.982583135	0.048769363	-0.058682086	-0.000160356	-0.058682086	-0.000160356
X Variable 3	0.003078322	0.006349071	0.484846071	0.628310891	-0.009440633	0.015597277	-0.009440633	0.015597277
X Variable 4	0.073701459	0.013170952	5.595757717	7.09234E-08	0.047731273	0.099671645	0.047731273	0.099671645

4- Apple (AAPL)

Table 11: Apple modified ANOVA Table

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.800342678
R Square	**0.640548402**
Adjusted R Square	0.633430549
Standard Error	0.034162553
Observations	207

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	0.420110505	0.105027626	89.99179451	8.654E-44
Residual	202	0.235750166	0.00116708		
Total	206	0.655860672			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.002998898	0.002398413	1.250367573	0.212611802	-0.001730239	0.007728035	-0.001730239	0.007728035
X Variable 1	1.006230547	0.055389327	18.16650613	2.35902E-44	0.897015124	1.115445969	0.897015124	1.115445969
X Variable 2	-0.020240885	0.018748118	-1.079622224	0.281597829	-0.057208	0.01672623	-0.057208	0.01672623
X Variable 3	-0.023884618	0.009477518	-2.520134392	0.012504744	-0.042572174	-0.005197063	-0.042572174	-0.005197063
X Variable 4	0.01974341	0.018603784	1.061257734	0.289839984	-0.016939111	0.05642593	-0.016939111	0.05642593

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5- Amazon (AMZN)

Table 12: Amazon modified ANOVA Table

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.78095663
R Square	**0.609893257**
Adjusted R Square	0.602168371
Standard Error	0.036807551
Observations	207

ANOVA

	df	SS	MS	F	Significance F
Regression	4	0.427853996	0.106963499	78.95174861	3.20699E-40
Residual	202	0.273668755	0.001354796		
Total	206	0.701522751			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.002973767	0.002579899	1.152667944	0.250408927	-0.00211322	0.008060754	-0.00211322	0.008060754
X Variable 1	1.071390788	0.061668277	17.37345107	5.85844E-42	0.949794674	1.192986901	0.949794674	1.192986901
X Variable 2	0.016896266	0.025308795	0.667604544	0.505148044	-0.033007043	0.066799576	-0.033007043	0.066799576
X Variable 3	-0.003746872	0.010158057	-0.368857149	0.712620519	-0.023776298	0.016282555	-0.023776298	0.016282555
X Variable 4	-0.071319949	0.020996171	-3.396807452	0.000820981	-0.112719723	-0.029920174	-0.112719723	-0.029920174

6- IBM (IBM)

Table 13: IBM modified ANOVA Table

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.885697052
R Square	**0.784459268**
Adjusted R Square	0.780191135
Standard Error	0.022091884
Observations	207

ANOVA

	df	SS	MS	F	Significance F
Regression	4	0.358804545	0.089701136	183.794463	3.89766E-66
Residual	202	0.098586373	0.000488051		
Total	206	0.457390918			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.000239265	0.001548156	0.15454827	0.877331761	-0.002813354	0.003291884	-0.002813354	0.003291884
X Variable 1	0.947910195	0.036989865	25.62621378	2.13141E-65	0.874974416	1.020845975	0.874974416	1.020845975
X Variable 2	0.015027291	0.016037915	0.936985355	0.34988498	-0.016595906	0.046650489	-0.016595906	0.046650489
X Variable 3	-0.006819157	0.006116547	-1.114870469	0.266230578	-0.018879625	0.005241311	-0.018879625	0.005241311
X Variable 4	-0.028013604	0.014611099	-1.917282443	0.056612901	-0.056823439	0.000796231	-0.056823439	0.000796231

When we start having a closer look on the processed data from the regressing of the new added behavioral variables to the adjusted required rate of return we will see that all statistical numbers have improved, as shown in the below tables;

1- Citi group (C)

Table 14: Citi Group Change in Regression Statistics

Regression Statistics		*Regression Statistics*	
Multiple R	0.721284636	Multiple R	0.794426058
R Square	**0.520251526**	**R Square**	**0.631112761**
Adjusted R Square	0.517911289	Adjusted R Square	0.623808063
Standard Error	0.033156374	Standard Error	0.029289252
Observations	207	Observations	207

2- Goldman Sachs (GS)

Table 15: Goldman Sachs Change in Regression Statistics

Regression Statistics		*Regression Statistics*	
Multiple R	0.825588018	Multiple R	0.844004824
R Square	**0.681595576**	**R Square**	**0.712344143**
Adjusted R Square	0.680042384	Adjusted R Square	0.706647988
Standard Error	0.026140813	Standard Error	0.025030378
Observations	207	Observations	207

3- Google (GOOGL)

Table 16: Google Change in Regression Statistics

Regression Statistics		*Regression Statistics*	
Multiple R	0.878674164	Multiple R	0.896577973
R Square	**0.772068286**	**R Square**	**0.803852062**
Adjusted R Square	0.770956424	Adjusted R Square	0.799967944
Standard Error	0.024590517	Standard Error	0.022980443
Observations	207	Observations	207

4- Apple (AAPL)

Table 17: Apple Change in Regression Statistics

Regression Statistics		*Regression Statistics*	
Multiple R	0.790662546	Multiple R	0.800342678
R Square	**0.625147261**	**R Square**	**0.640548402**
Adjusted R Square	0.623318711	Adjusted R Square	0.633430549
Standard Error	0.034630536	Standard Error	0.034162553
Observations	207	Observations	207

5- Amazon (AMZN)

Table 18: Amazon Change in Regression Statistics

Regression Statistics	
Multiple R	0.765342035
R Square	**0.58574843**
Adjusted R Square	0.583727691
Standard Error	0.037650958
Observations	207

Regression Statistics	
Multiple R	0.78095663
R Square	**0.609893257**
Adjusted R Square	0.602168371
Standard Error	0.036807551
Observations	207

6- IBM (IBM)

Table 19: IBM Change in Regression Statistics

Regression Statistics	
Multiple R	0.882799449
R Square	**0.779334868**
Adjusted R Square	0.778258453
Standard Error	0.022188794
Observations	207

Regression Statistics	
Multiple R	0.885697052
R Square	**0.784459268**
Adjusted R Square	0.780191135
Standard Error	0.022091884
Observations	207

The results show that R-squared and Adjusted R-squared improved in all the six chosen stocks after the addition of the behavioral factors. Statistically $\mathbf{R^2}$ measures how well data points fit the regression line; Adjusted $\mathbf{R^2}$ similarly measures goodness of fit while adjusting for the number of predictors. Adding meaningful variables to the model increases adjusted $\mathbf{R^2}$. Conversely, the standard error decreased across all six stocks, confirming that incorporating behavioral variables enhances the model's predictive accuracy and generalizability.

6. Limitations

The main limitation to this study was the availability of volatility indices to different stocks in the market. This variable is crucial to be added as an enhancement to the CAPM equation. Volatility index is mainly calculated using both calls and puts options; hence, it has a forward looking to the stocks and is used as a measure of risk to investors.

7. Conclusion

Behavioral finance is a growing field whose main aim is to demonstrate how investors' behaviors affected by each one's psychological, social, and emotional aspects, can affect their investments' decisions combined with financial and economic factors taken into consideration. This paper's main goal was to show that this is possible by adding quantified variables representing investors' behaviors to the CAPM equation to see its effect on the required rate of return. By running statistical regression on those factors and their effect on the modified required rate of return, we could conclude that investors' irrational actions can have an influence on their economic decisions, which will consequently influence market prices and returns.

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