A Behavioral Approach To Stock Pricing

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ABSTRACT

Recent literature in behavioral finance has contradicted the notion of efficiency of markets. Greater emphasis on how psychological biases influence both the behavior of investors and asset prices has led to a strong debate among proponents of behavioral finance and neoclassical finance. This has created the need to study how psychology affects financial decisions in households, markets and organizations. This study conducts a pooled ordinary least squares (OLS) model using the fixed effects estimator to investigate the linkage between investor sentiment and stock prices for 35 firms belonging to three different industries over a time period of 56 years, from 1950 to 2005. The findings suggest that investor sentiment does not significantly affect the stock prices in this sample.

Keywords: Market Efficiency, Stochastic Discount Factor Model, Behavioral Finance, Investor Sentiment Function, Stock Prices

INTRODUCTION

Several events in the world of finance, such as the Great Crash of 1929, the Black Monday crash of October 1987, the internet bubble of the 1990s, and the recent financial turmoil in October 2008, not only caused a dramatic change in stock prices but also challenged the explanation offered by neoclassical finance models. The standard finance model, in which "unemotional investors always force capital market prices to equal the rational present value of expected future cash flows," does not seem to offer perfect insight into asset pricing anomalies (Baker and Wurgler 2007, p. 129). Because the recent financial turmoil that took place in 2008 reflected highly volatile swings of sentiment in both equity and debt markets, it seems timely to define a human sentiment function in a stochastic discount factor (SDF) model. Consequently, researchers have proposed some key behavioral theories to supplement the existing finance model and better predict asset returns in the market. These studies are based on experimental psychology literature to explain investor behavior.

Both behavioral finance and neoclassical finance have different implications for asset pricing and the relationship between risk and return. Recent literature in financial economics has contradicted the notion of market efficiency and recognized the influence of psychological biases on the behavior of an investor and on asset prices. The purpose of this study is to delve into the fundamental theories of asset pricing – both neoclassical and behavioral – to better understand the linkage between investor sentiment and asset prices. According to Anderson, Ghysels and Juergens (2005), investor sentiment, defined as erroneous beliefs about future cash flows and risks, significantly affects the prices of all assets. This paper will provide the necessary framework for understanding the behavioral asset pricing model (which includes human sentiment) and the traditional neoclassical pricing model (which excludes human sentiment) to find out which model better explains the pricing of an asset. The study uses 35 large sample firms belonging to three different industries (healthcare, financial services, and aviation and defense) and conducts an empirical analysis on the effect of the investors' sentiment measure on stock prices over a time period of 56 years, from 1950 to 2005.

The first part of the paper presents a summary of the literature related to the relevant theories, primarily the Efficient Market Hypothesis (EMH), behavioral Stochastic Discount Factor Model (SDF) and empirical measurements of the investor sentiment function. The second half of the paper discusses the nature of the econometric model constructed, reviews the comprehensive methodology to test the model and analyzes the results to determine the effect of an investors' sentiment index on stock prices.

A BRIEF REVIEW OF THE LITERATURE

For quite some time, the efficient capital market hypothesis, a centerpiece of neoclassical financial theory, has dominated the working mechanism of financial markets. This hypothesis, first promulgated by Eugene F. Fama (1970), claims that financial markets price assets precisely at their intrinsic worth given all publicly available information. Fama argues that an efficient market is one in which firms can make production-investment decisions and investors can choose among the securities that represent ownership of firms' activities under the assumption that security prices at any time fully reflect all available information. This implies that the price of a company' stock always accurately reflects the company's value given the information available on the firm's earnings and its business prospects. The argument for rational investors in a competitive market has resulted in several empirical works that aim to test the market efficiency hypothesis. Jegadeesh and Titman (1993) and Poterba and Summers (1988) support the rational response of market prices to changes in discount rates and the market efficiency hypothesis.

Though several empirical works strongly confirm market efficiency, some of the research is difficult to reconcile with the efficient market hypothesis. Financial economists also offer a different insight into some of the most puzzling phenomena in empirical finance and argue that there is some concrete evidence for inefficient markets, primarily in the form of systematic errors in the forecasts of stock analysts. Lakonishok, Shleifer, and Vishny (1995) argue that analysts extrapolate past performance too far into the future and, consequently, overprice firms with recent good performance and underprice firms with recent poor performance. This accounts for the reversal effect when market participants recognize their errors. Since firms with sharp drops in price may be small or have high book-to-market ratios, their explanation is consistent with the small-firm and book-to-market effects. A study by La Porta (1996) offers a similar explanation. La Porta finds that the equity of firms for which analysts expect low growth rates in earnings actually beat those with high expected earnings growth. Therefore, several anomalies regarding fundamental analysis have brought into question the validity of market efficiency.

To address the existence of anomalies, researchers have attempted to incorporate behavioral finance into the standard finance model. For instance, Delong et al. (1990, p. 703) "present a simple overlapping generations model of an asset market in which irrational noise traders with erroneous stochastic beliefs both affect prices and earn higher expected returns." The authors also argue that the random nature of noise traders' beliefs creates variability in the price of assets that prevents unemotional arbitrageurs from aggressively betting against them. Therefore, some of the results have raised questions about the non-existence of noise traders in the market. This has necessitated the understanding of behavioral theories to better understand investor behavior and asset pricing. A growing body of psychological evidence suggests that people's beliefs are often predictably in error. Several studies regarding some of the biases in human beliefs, such as forecasting and overconfidence, have attempted to shed insight on how human investors make systematic errors. For instance, De Bondt (1993) shows that investor forecasts may hold on the price at which they buy a security. Similarly, Daniel, Hirshleifer and Subrahmanyam (2001) suggest that investors exhibit overconfidence and self-attribution bias. As a result, proponents of behavioral asset pricing have attempted to show that asset prices reflect sentiment.

Recent research studies strive to model investor sentiment. Baker and Wurgler (2007) study the theoretical effects of investor sentiment on different types of stocks. They create the Sentiment Seesaw with stocks on the x-axis according to how difficult they are to value and arbitrage, and the prices that denote fundamental values on the y-axis. The Seesaw shows that "high sentiment should be associated with high stock valuations, especially for the stocks that are hardest to value and arbitrage, and low sentiment works in the opposite direction" (Baker and Wurgler 2007, p. 133). With no sentiment, stocks are said to be correctly priced at the equilibrium price. Similarly, Barberis, Shleifer and Vishny (1998) present a model of investor sentiment to show how the beliefs of an investor affect both prices and returns. The model is based on psychological evidence that "people pay too much attention to the strength of the evidence they are presented with and too little attention to its statistical weight" (p. 332). These works represent only a small segment of the substantial research done on modeling investor sentiment and its effect on asset pricing.

Regardless of the challenges associated with empirical measurements of behavioral asset pricing models, financial economists have discovered different ways through which investor sentiment and its effects can be quantified. Some of the studies empirically estimate the human sentiment function. For instance, Ait-Sahalia and Lo (1998) calculate the empirical stochastic discount factor (SDF) and compare the prediction of the model with the returns on the Standard & Poor's 500 Index (Shefrin 2008, p. 10). They find the sentiment function to be the difference between logarithms of the behavioral SDF and the traditional neoclassical SDF. Similarly, Rosenberg and Engle (2002) first restrict the SDF to the traditional neoclassical model and then use a free form Chebyshev polynomial procedure with no restriction to test whether the empirical SDF is behavioral or not. Their empirical findings suggest that the SDF is behavioral.

Some studies use as time-series conditioning variables a number of proxies for sentiment. Baker and Wurgler (2007) form a composite index of sentiment based on common variations in six underlying proxies for sentiment: the closed-end fund discount, New York Stock Exchange (NYSE) share turnover, the number of Initial Public Offerings (IPOs) and the average first-day returns, the equity share in new issues, and the dividend premium, and they measure the sentiment proxies annually from 1930 to 2005. The final result is that their sentiment index successfully captures the level of sentiment for different key economic periods. For instance, during the late-1990s bubble in technology stocks, "sentiment among investors was broadly high" (Baker and Wurgler 2007, p. 141). Their result is compatible with such economic periods of bubbles and crashes.

Substantial research shows that modern asset pricing is built around the notion of investor sentiment. Further, significant evidence of puzzling phenomena in finance opposes the underlying assumptions of the EMH. This has motivated researchers to add sentiment functions in the SDF model and observe whether the behavioral asset pricing theory better explains the historical asset pricing patterns. As a result, the current study investigates whether significant linkage exists between investor sentiment and stock prices, employing the sentiment index of Baker and Wurgler.

DATA

The data take into account key financial variables from Standard & Poor's Compustat for 35 large companies (shown in Table 1) belonging to three different industries (health care, aerospace and defense, and financial services) from 1950 to 2005. One of the primary independent variables used in the model, the composite index of investor sentiment (SI), is based on common variations in three underlying proxies for sentiment: the closed-end fund discount (CEFD), the equity share in new issues, and the lag of detrended log New York Stock Exchange (NYSE) share turnover (Baker and Wurgler 2006, p. 1672). CEFD is the average difference between the net asset values of closed-end stock fund shares and their market prices. NYSE share turnover, synonymous with liquidity, is based on the ratio of reported share volume to average shares listed, both from the NYSE Fact Book. Because "irrational investors actively participate in a market with short-sales constraints and add liquidity only when they are optimistic," high liquidity is considered a sign of overvaluation (Baker and Wurgler 2006, p. 1656). Similarly, the equity share is defined as gross equity issuance divided by gross equity plus gross long-term debt issuance, using data from the Federal Reserve Bulletin. The share of equity issues in total equity and debt issues is a significant measure of financing activity that captures sentiment (Baker and Wurgler 2000).

Table 1: List Of Sample Firms

Aerospace and Defense Industry	Financial Services Industry	Healthcare Industry
Honeywell International Inc., United Technologies Corp., General Dynamics Corp., Raytheon Company, Textron Inc., Ball Corporation, Eaton Corporation, Boeing,Northrop Grumman Corporation, Lockheed Martin Corporation and Danaher Corporation	Target Corporation, United Parcel Services, Inc., Wells Fargo & Company, Bank of America, State Street Corp., The Hanover Insurance Group Inc., US Bancorp, The Bank of New York Mellon Corporation, Deere and Company and American Express Company	Johnson and Johnson, CVS Caremark, McKesson Corporation, Bristol-Myers Squibb Company, Kimberly-Clark Corporation, Medtronic Inc., Owens & Minor Inc., Pfizer, Merck, Eli Lilly & Co., Baxter International, Wyeth, Abbott Laboratories and American Independence Corp.

ECONOMETRIC METHODOLOGY

This study conducts a pooled ordinary least squares (OLS) model using the fixed effects estimator to determine the linkage between investor sentiment and the price of a stock. The model also includes year dummies for all years but the last and dummies for the aerospace and financial industries. When employing the fixed effects estimator, the model does not estimate the effect of any variable whose change across time is constant. Under a strict exogeneity assumption on the explanatory variables, the "fixed effects estimator is unbiased" (Wooldridge 2009, p. 482). In other words, the idiosyncratic error in the model is uncorrelated with each explanatory variable across all time periods. In this model, we have NT = 35*56 = 1960 total observations. However, for each cross-sectional observation i, we lose one degree of freedom due to the time-demeaning effect. This results in the appropriate degrees of freedom as NT-N-K, where K is the number of independent variables. Equation (1.1) shows the OLS empirical model used in this study.

$$PRI = f\,(SI, GPGR, LIA, LEV, ROE, DIV, CF, D_{1950-2004}, D_{aero,fin}) \quad (1.1)$$

The price of a stock (PRI) is defined as a function of the independent variables investor sentiment index (SI), gross profit growth rate (GPGR), current ratio (LIA), debt ratio (LEV), return on equity (ROE), dividends per share (DIV), free cash flow to equity (FCF), dummy variables for the first 55 years ($D_{1950-2004}$) and dummy variables for the aerospace and financial services industry ($D_{aero,fin}$). Because Louis Navellier (2007) argued that expanding operating margins, strong cash flow, earnings growth and high return on equity are some of the factors that drive stellar stock price performance, the model was created to include some of these variables. This regression analysis was conducted for the entire sample. Numerical adjustments, made to improve the fit of the model and the significance of the independent variables, were made as necessary. (See Appendix I for details.)

RESULTS

The coefficients and t-statistics for each independent variable (excluding that of the dummy variables for the sake of brevity) in the regression models are shown in Table 2. Model 1 includes SI, and Model 2 does not. To alleviate the problem of non-normality of errors, the dependent variable PRI was transformed to the logarithm of the stock prices, log (PRI). The t-statistic estimating the role of the investor sentiment index in determining the price of a stock (PRI) is statistically insignificant for the entire sample (See Table 2). Model 1 reports that log(PRI) decreases by 0.13 times for every unit increase in investor sentiment, quantified by SI.

Table 2: Pooled Ols Regression Results For The Entire Sample (Log Price As The Dependent Variable)

	MODEL ONE			**MODEL TWO**		
Variable	Coefficient	t-Statistic	Prob.	Coefficient	t-Statistic	Prob.
C	4.209052	20.69378	0	4.275128	23.20189	0
SI	-0.135053	-0.614047	0.5393			
GPGR	0.062147	1.861143	0.063	0.063427	1.903929	0.0572
LIA	-0.095876	-2.833491	0.0047	-0.091729	-2.688676	0.0073
LEV	-0.561687	-2.35381	0.0188	-0.564071	-2.361398	0.0184
ROE	0.014906	2.606912	0.0093	0.011981	3.311952	0.001
DIV	0.016922	1.686605	0.092	0.016929	1.682334	0.0928
FCF	3.07E-06	0.426774	0.6696	2.73E-06	0.380151	0.7039
AR(1)	0.773038	33.17002	0	0.77287	33.15414	0
R-squared	0.727115			0.727003		
Adjusted R-squared	0.712558			0.71274		
F-statistic	49.94728			50.97072		
DW Statistic	2.112843			2.11213		

Results show that sentiment essentially has no significant role in predicting stock prices. Because previous research has not completely proven this effect, a comparable statistic is difficult to find in the U.S. equity market. Furthermore, this finding is inconsistent with work done by Tsuji (2006) on the characteristics of investor sentiment in Japan. Tsuji shows that "investors' positive sentiment towards future stock markets successfully predicts the one-month ahead stock price dynamics" (Tsuji 2006, p. 356). However, it is important to note that Tsuji uses a different approach to quantifying investor sentiment in Japan; the six sentiment variables used in his regression model are as follows: the difference between the average of Japanese investors' future one month prediction of the NIKKEI 225 index level and the realized NIKKEI 225 index level at time t (Δ NKF), the standard deviation of investors' one-month ahead positive (negative) predictions for the NIKKEI 225 index level forecasted at time t (SD), the index of the investors' future equity investment stance constructed by Quick Corp. (STANCE), the one-month change of the variable STANCE (ΔSTANCE) and another variable constructed by the Quick Corp. that provides data on the future equity investment stance of Japanese investors (EQALL). The coefficient for the constant term (C) for both models is significant at the 1% level.

The coefficients for some of the independent variables exhibit statistical significance at the 1% level in both models 1 and 2. To exemplify, ROE, LIA and LEV all show statistically significant relationships with the stock prices. The coefficients for the debt ratio (LEV) and the current ratio (LIA) are both inexplicably negative, yet statistically significant at the 1% level. As expected, the coefficients for GPGR, DIV and FCF show positive signs, yet are not statistically significant at the 5% level.

The autoregressive term [AR(1)] is positive and statistically significant at the 1% level. Though the models are free of the major econometric problems (serial autocorrelation and heteroskedasticity), high correlation between LIA and LEV exists in both of the models. Furthermore, though the Jarque-Bara stat decreased to 65 from 384 when PRI was changed to log (PRI), even transformation of the variables did not completely alleviate the problem of non-normality. The R-squared and adjusted R-squared statistics are all above 0.7 for each model. This value means that models 1 and 2 explain 72% of the variation in price of a stock for the entire sample. The F-statistic is also above the critical value at the 1% level for both model 1 and 2. Because no significant difference exists between the R-squared statistics in the models, the results suggest that investor sentiment fails to give significant additional explanatory value.

CONCLUSION

This study has examined the relationship between investor sentiment and the price of a stock over a time period of 56 years, from 1950 to 2005. The entire sample consisted of 35 firms belonging to three different industries: aerospace and defense, financial services and healthcare. To the authors' knowledge, this is the first research to compare the results between the traditional asset pricing model (with no investor sentiment index) and the behavioral asset pricing model (with a investor sentiment index) for such a comprehensive period of time. Because behavioral finance models cannot be tested as easily as traditional asset pricing models, relatively little empirical evidence exists to support the significance of sentiment in finance. However, this study applies Baker and Wurgler's investor sentiment index that successfully captured major fluctuations in sentiment during economic periods of bubbles and crashes (Baker and Wurgler 2006). This study also takes the origin of investor sentiment as exogenous and focuses on its empirical effects on the price of a stock.

The findings of this study, however, leave room for some criticisms. One difficulty in the regression model is that the coefficient for current ratio and debt ratio in the entire sample showed a negative sign. This problem can possibly be alleviated by increasing the sample size. Secondly, the model would give a better picture of the effect of the sentiment index on the price if additional industries were included. This was not a feasible option due to inadequate data on most of the large financial companies. However, this can be incorporated in future research in the field of behavioral finance. Third, one of the major econometric problems, non-normality of the error terms, still exists in the model for the entire sample. Though transformation of the variables was conducted, the problem could not be fixed. Because variable elimination was not preferred in this case study, the results are as accurate as they could be, given the data compiled. These are some points to be considered in undertaking a similar empirical project pertaining to behavioral finance in the future.

This study has attempted to shed some light on incorporating an empirically calculated investor sentiment function in a traditional neoclassical asset pricing model. The primary finding of this study is that there exists a statistically insignificant linkage between investor sentiment and the price of a stock. This research does not offer strong evidence that the behavioral asset pricing model better explains the determinants of the price of a stock than the traditional neoclassical asset pricing model.

AUTHOR INFORMATION

Jayash Paudel is a 2010 Mathematical Economics graduate from Colorado College whose senior thesis provided the basis for this work.

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APPENDIX I

The normality of the error term is a primary econometric issue for the OLS regression equations. The Jarque-Bera statistic indicates non-normality problems. If the Jarque-Bera statistic is greater than the critical chi-squared value of 5.99 for the 5% significance level, then the error terms have a non-normal distribution (Wooldridge 2009). If the residuals don't have a normal distribution, the T-tests and F-tests statistics for the model will not be dependable (Pindyck and Rubinfeld 1998, p. 88-89). The data sets used in this model were tested with a Jarque-Bera statistic to detect any non-normality error distribution.

One of the primary assumptions of regression of panel data is that the error terms in the many different observations are not related (Eastman 1984, p. 83-84). When serial correlation exists, the error terms of different observations across time are correlated. This problem may lead to an over-estimate or an under-estimate of the partial regression coefficients. The Durbin-Watson test is performed by comparing the calculated Durbin-Watson statistic to the upper and the lower values of the statistic in the D-W Table according to the number of observations and the number of independent variables. A value of 2 for the Durbin-Watson statistic suggests that there is no strong evidence of autocorrelation in the residuals of the estimated equation. If uncorrected, serial correlation in the residuals will lead to an incorrect estimate of the standard errors and invalid statistical inferences for the coefficients of the equation. To solve this problem, an autoregressive term was included in the OLS model, and the null hypothesis of no serial correlation was rejected according to the Durbin-Watson test statistic (Fair 1970). The autoregressive term is displayed in the table as AR(1).

The White test is conducted to test the problem of heteroskedasticity. This problem involves an irregular variance in the constant error, which is a violation of homoskedasticity (Pindyck and Rubinfeld 1998, p. 146). When the assumptions of the linear regression model are accurate, OLS provides unbiased and efficient estimates of the set parameters. Heteroskedasticity arises when the variance of the errors fluctuates across observations. If the error terms are heteroskedastic, the OLS estimator remains unbiased but is no longer efficient. In other words, estimates of the standard errors are inconsistent, thus resulting in misleading conclusions (Long and Ervin 1998, p. 2). When the model contains $k = 9$ independent variables, the White test is based on an estimation of eighteen regressors. If the White Test statistic is smaller than the critical Chi-square value (with degrees of freedom = 18 at a 5% significance level), the model is free of the problem of heteroskedasticity.

Multicollinearity rejects the assumption that all independent variables individually affect the dependent variable. When two or more variables are correlated with one another or have the same predictive power with respect to the dependent variable, multicollinearity exists. This makes identifying the individual effects of independent variables on the dependent variable more difficult. A correlation matrix of all the independent variables is run to detect correlation among different independent variables. If any of the off-diagonal values are bigger than 0.5, transformation of some of the independent variables is conducted to solve this problem.