

Spring 5-10-2009

Price Multiples as Indicators of Stock Price Movement: Evidence from the 21st Century

Jason Zamichiei
jzamichiei@gmail.com

Follow this and additional works at: https://opencommons.uconn.edu/srhonors_theses

 Part of the [Accounting Commons](#), and the [Portfolio and Security Analysis Commons](#)

Recommended Citation

Zamichiei, Jason, "Price Multiples as Indicators of Stock Price Movement: Evidence from the 21st Century" (2009). *Honors Scholar Theses*. 65.

https://opencommons.uconn.edu/srhonors_theses/65

Price Multiples as Indicators of Stock Price Movement:

Evidence from the 21st Century

Jason Zamichiei

Advised By: George Plesko

In partial fulfillment of the requirements of the Honors Scholar
distinction for the University of Connecticut.

I. ABSTRACT

This paper examines the use of price multiples to predict stock returns. The price to earnings, price to sales, and price to book value multiples are regressed against annual stock returns to determine if a relation between the magnitude of the multiples and returns exists. The results indicate that there are relations between low price to earnings and price to sales multiples and positive returns. I find no evidence that the price to book value multiple can be used to develop a stock buying strategy.

II. INTRODUCTION

In his book, What Works on Wall Street, O'Shaughnessy states that,

We make the simple complex, follow the crowd, fall in love with the story, let our emotions dictate decisions, buy and sell on tips and hunches, and approach each investment decision on a case-by-case basis, with no underlying consistency or strategy (O'Shaughnessy 17-18).

With all of these pitfalls, investors can, and often do, make misguided decisions, which can lead to sub-optimal returns. As O'Shaughnessy points out, even mutual fund managers often fail to beat indices such as the S&P 500. Of all the mutual funds belonging to the Morningstar database, about 80% failed to produce higher returns than the S&P 500, during the 1990s. He attributes this, in part, to investing techniques such as reviewing forecasts, speaking to management, and financial analyses of a company. These types of techniques are the origins of tips and stories, and emotions are free to affect judgment. In two studies on fund managers, the characteristic common to the highest performers was choosing and adhering to a well-defined strategy (2-9).

O'Shaughnessy outlines desirable characteristics of investment strategies. First, there must be clearly stated rules. This means that nothing is open to interpretation and anyone following the strategy will come to the same buy or sell conclusion by following the rules. Second, the rules must be consistently applied over time. Deviating from the rules is the equivalent to a change of strategies, and thus year to year comparability is lost. Breaking the rules also allows outside factors, which the strategy is designed to combat, to affect the decision making process. Third, a good strategy will produce similar

results in the long-term, while a strategy that only applies to a short period of time has limited value to investors. O'Shaughnessy gathered evidence on price multiples from 1951 to 1994, and makes recommendations on how to form investment strategies (6-9). This paper examines the use of the price to earnings multiple, the price to sales multiple, and the price to book value multiple, to reach a buy or sell decision for stocks in the 21st century. They are referred to as the P/E multiple, the P/S multiple, and the P/BV multiple, respectively

For the analysis, data from 2000 to 2007 is examined. The price to earnings, price to sales, and price to book multiples are ranked at the industry level, the highest and lowest deciles are examined, the effects of having price multiple values in either the highest or lowest deciles are tested. The results indicate that stocks with low price to earnings multiples have small, positive percent changes in price. Stocks with high price to earnings multiples tend to have small, negative percent changes in price. Low price to sales ratios tend to indicate high, positive percent changes in price, while high values indicate negative percent changes. Low price to book value multiples are not clear indicators of percent changes of stock price, but high values tend to indicate small percent changes.

III. PRICE MULTIPLES EXAMINED

A. The P/E Multiple

The price-to-earnings multiple, also known as the P/E multiple, price-to-earnings ratio or PE ratio, is the most popular price multiple for stock valuation. The P/E multiple is defined as the current market price of a stock divided by earnings per share. The

earnings per share value is calculated using the earnings from the prior year. The formula is as follows:

$$\text{P/E multiple} = (\text{Market Price} / \text{Earnings Per Share})$$

While the forecasted earnings per share value for the upcoming year can also be used in the equation, the prior year's earnings per share will be used for all P/E multiple analyses (Thomsett 70-71). The reason for this is to remove any analyst bias from the regression results.

The result given by the P/E multiple formula is a number which represents the number of times the stock sells above earnings. For example, on March 9, 2009, the price of one share of Toyota stock was \$57.68 and EPS was \$4.20. The P/E multiple is, therefore, calculated to be 13.73 (Yahoo Finance). This means that investors are willing to pay 13.73 times Toyota's earnings for each share. A higher P/E multiple can be interpreted as being more desirable than a low multiple. Investors are willing to pay more for earnings when they believe future earnings will be higher. Thus, stocks of companies that are expected to grow will have their prices bid up. When future earnings increase, the price of stock, and thus the return to current investors, will increase. The opposite is true for stocks with a low P/E multiple. Investors will be less willing to pay for earnings when they do not expect future growth to be significant. As a result, the P/E multiple is lower for these companies because investors do not expect to receive large returns from owning these stocks (Matras 1-2).

One advantage of the P/E multiple is that it serves as a benchmark. It can be compared to historical P/E multiples of the same company or to current P/E multiples of other companies in an industry, or the entire market. First, the P/E multiple can be

compared to historical figures of the same firm. An increasing multiple can indicate growth and higher returns. When using the P/E multiple to compare to other firms in an industry, companies with growth potential, those with a higher P/E multiple, and thus possible high returns for investors can be discovered. Also, comparisons can be made to the entire market. The same type of analysis is done with the market as a benchmark. The difference between the choices of benchmark is based on external factors. For example, if a firm has stable growth, its historical P/E multiple may be the best benchmark. If the industry is significantly different than other industries, for example in terms of capital structure, then the industry should be used. The market can give a relative picture of possible growth of the firm. During periods where the entire market grows, the average P/E value for the market will increase. Monitoring changes in a firm's P/E and comparing it to the market P/E can help determine potential increases in price (Dorsey 131-132).

One disadvantage of the P/E multiple is that it can be non-comparable, which will reduce its ability to serve as a benchmark. First, the decision to capitalize or expense will affect reported earnings. For example, a manufacturing firm that purchased equipment will capitalize the total cost and depreciate over several years. A pharmaceutical company will expense all research and development costs associated with developing a new drug, thus lowering earnings. Here, cross industry comparisons or a market comparison may have limited value. Also, cyclical earnings patterns will distort the P/E multiple as earnings fluctuate. If the previous year had high earnings, the 12-month earnings per share will increase in the current year. This would, falsely, indicate a potential for growth. Finally, selling a division or assets at a profit will inflate earnings. With inflated earnings, the P/E multiple will be lower than before the sale. To improve

comparability, the positive effect on earnings from the sale should be deducted (132 – 134).

Another disadvantage is if a company has negative earnings. In this case, the P/E multiple cannot be easily interpreted. The result would imply that investors are only willing to pay a negative sum for earnings. This is clearly not true because the market price must be positive (Thomsett 71).

B. The P/S Multiple

The second multiple to be examined is the P/S multiple, or price-to-sales multiple. This multiple is calculated by dividing the current market price of a share of stock by the sales per share. The formula is as follows:

$$\text{P/S multiple} = (\text{Current Market Price} / \text{Sales Per Share})$$

This formula produces a number which represents the amount investors are willing to pay for a dollar of sales. All else equal, lower value is preferred to a high value because investors are paying less for each dollar of sales.

One advantage of the P/S multiple is that it is more stable than the P/E multiple. Sales are not as susceptible to cycles as earnings and are not affected by transactions such as buying or selling assets and divisions. Thus, even in the presence of these business activities, sales will be relatively constant. Also, earnings can be manipulated to meet analyst forecasts. While this can also be done with sales, earnings are manipulated more often. The more stable sales figure makes the P/S multiple well suited to value companies with volatile or negative earnings. If a company has negative earnings, a P/E multiple

cannot be meaningfully calculated, but the P/S multiple can. Motorola can be used to illustrate this advantage.

Motorola	1998	1999	2000	2001	2002
P/E multiple	n/a	119.7	34.9	n/a	n/a
P/S multiple	1.3	3.2	1.2	1.1	0.7

Motorola posted negative earnings in 1998, 2001, and 2002, and has no P/E multiple for these years. When it did have earnings, they were not stable, which made the P/E multiples volatile. The P/S multiples, however, can be calculated for each year, and are fairly stable. In this case, the P/S multiple can be used as a benchmark to compare Motorola to other companies and provides more information.

One disadvantage of the P/S multiple is that it has little meaning if information about profitability is not known. For example, companies in industries with low profit margins will have low P/S multiples. Likewise, companies in industries with high profit margins have higher P/S multiples. When comparing the P/S multiple of firms of different profitability, the one with the lower P/S multiple will look like it is a better buy because its sales cost less. This type of comparison cannot be made. Comparisons across industries can only be made if profit margins are similar, otherwise an incorrect conclusion will be drawn (Dorsey 128-129).

C. The P/BV Multiple

The final multiple I examine is price to book-value. This multiple is calculated by dividing the current market price by the per share book value of the company. The formula is as follows:

$$\text{P/BV multiple} = (\text{Current Market Price} / \text{Book Value Per Share})$$

Book value per share is defined as the book value of assets minus the book value of liabilities. To convert this number to a per share basis, it must be divided by the total shares outstanding.

A low P/BV multiple is preferred to a high value, but this rule does not hold true for all cases. For example, a P/BV multiple less than one means that the stock is selling for less than its book value. One interpretation could be that it is undervalued because the company can be purchased for less than its liquidation value (Durell 1-2). The second interpretation is that the low value indicates problems with the company. For example, it could indicate that assets are overstated on the balance sheet. This could mean that the assets may not be able to produce optimal returns for the firm (English 27).

One advantage of the P/BV multiple is that it is very good for valuing financial services firms. These firms generally have large amounts of assets, which are the source of cash flows, and are valued with mark-to-market accounting. Each quarter, they are revalued for impairments or appreciation. Therefore, the current book values means there is little distortion of the ratio.

One disadvantage is that the P/BV multiple can be distorted by various accounting factors. First, long term assets, such as land, are reported at original cost. Over time, these assets may appreciate in value, but this will not be updated on the balance sheet. Therefore, the book value will be too low, causing the ratio to be overstated. Also, the purchase of another company can result in an inflated book value. The higher book value will result in a lower value for the ratio. The excess value paid over book value for the company is recorded as goodwill. Goodwill is not a tangible asset that can be liquidated.

Often, this goodwill is determined to be impaired and is written down. Sometimes companies will not include intangible assets in the book value calculation if these assets are material and will distort the ratio. Finally, companies with large amounts of intellectual property will have a lower book value, thus driving up the ratio. Intellectual property includes the employees who bring creativity and innovation to a company. Intellectual property is not recorded on the balance sheet, but it is expensed. It can be a large part of a company's assets, but are not in the book value (Durell 1-2).

Investors use multiples to predict future price movements because there is evidence supporting their ability to do so. Ken Fisher, in his book Super Stocks, focuses on the P/S multiple and how to use it to pick stocks with high returns. Today, variations of his strategy are used by investors. Beginning in 2003, John Reese, of Forbes, used a P/S multiple strategy to pick stocks and has had a 167.1% return, while the S&P 500 returned 33.3% (Reese 1-3). In 1997, James O'Shaughnessy, in his book, What Works on Wall Street, which outlines strategies for using all three types of ratios. He outlines the growth of an initial investment by picking stocks with high and low ratios over a period of time. O'Shaughnessy's evidence shows that investing in stocks with low multiples have, historically, resulted in the highest returns. He also shows how buying stocks with the undesirable multiple value will result in reduced gains, which are sometimes less than the market as a whole (O'Shaughnessy 1-9). Because there is considerable evidence for the use of these multiples, and because they have successfully been used for decades, they will be tested to see if they can indicate abnormal returns in today's market.

For this investigation, I collect data for the years 2001 to 2007. This range includes all years of the 21st century, beginning after the market reaction to 9/11, that did

not experience substantial economic losses. In 2008, the stock market suffered record losses and a majority of securities had negative returns.

IV. SAMPLE DESCRIPTION

The sample of firms was gathered using the Compustat fundamental annual database. All firms with an SIC below 6000 were selected. Financial and other service companies have SIC codes above 6000 and were not selected because of different accounting treatments and multiples cannot be directly compared between firms in these industries and those included in the sample. The sample was further narrowed by dropping observations with negative price to earnings and price to book value multiples. Negative P/E multiples are the result of negative earnings for the year. They were eliminated to improve comparability of data. Negative P/BV multiples were deleted for the same reason. Also, many of the P/S multiples were very low. All P/S multiples below .01 were deleted because these were extreme values and indicate problems with the companies. Other multiples did not have similar outliers. The goal with their omission was improved comparability.

The variables used for this analysis include *sich*, *sich2*, *PE*, *PS*, *PB*, *prankPX*, *PXhigh*, and *PXlow*. *Sich* is the four-digit standard industrial classification code, SIC, industry code used to classify observations into specific groupings. *Sich2* is the broad, two-digit SIC code used to rank observations. This two digit classification was used to increase the number of observations per industry by reducing the number of industries. The *PE* variable contains all of the P/E multiples for the sample. It is calculated by dividing the beginning of the year closing price of each stock by the prior year's earnings

per share. Earnings per share are stored under the variable epspx. PS and PB variables contain the sample P/S multiples and P/BV multiples for the sample, respectively. PS is calculated by dividing the current closing price by the prior year's sales per share. Sales per share are stored under the variable sale. PB is calculated by dividing the beginning of the year closing price by book value per share. Book value per share is stored as bkvlp. PrankPX is used to store the ranking, in percent form, of each multiple. PXhigh contains the highest 10% of the sample multiples within each industry. There are three of these variables, one for each multiple. PXlow contains the lowest 10% of the sample multiples. Observations were deleted if they were missing any of the data.

The final sample contains 12,324 observations. This ensures that the sample of firms examined by each multiple is the same and allows for comparison of results. Table 1 contains the descriptive statistics of this sample.

V. HYPOTHESIS

Each multiple is tested for their ability to predict the return on the stocks. Regressions are performed at a sample level, broad-industry level, and specific-industry level. For each, the following equation is estimated:

$$\text{Percent change in price} = \alpha + \beta(P/X)$$

The β in this equation gives the estimated percent change in price for the sample, depending on which of the three multiples is used. The equation for predicted change in price for the broad-industry level or the specific-industry level is:

$$\text{Percent change in price} = \alpha + \beta(PX) + \beta(PXlow) + \beta(PXhigh)$$

Here, the variable PX_{low} is composed of the value of a given multiple for firms in the lowest decile of the ranking of multiples. PX_{high} contains only firms in the highest decile of a ranking of the multiples.

A. P/E Multiple Hypothesis

The first multiple to be examined is the P/E multiple. It is hypothesized that firms with the highest P/E multiples will have the highest percent change in price, and firms with the lowest P/E multiples will have the lowest percent change in price, over a one year period. This hypothesis is based on the relation between the magnitude of this multiple and investors' beliefs of growth. Choosing the same time frame of annual percent change in price will also allow for a comparison of my results to O'Shaughnessy's study.

For the regression with all industries, the following equation is estimated:

$$\text{Percent change in price} = \alpha + \beta(\text{PE}) \quad (1a)$$

A positive β is expected because increasing values of P/E multiples are expected to result in higher returns. A positive β will indicate that there is a relation between high P/E multiples and returns, at the aggregate level. The equation that is estimated for selected industries is:

$$\text{Percent change in price} = \alpha + \beta(\text{PE}) + \beta(\text{PE}_{low}) + \beta(\text{PE}_{high}) \quad (1b)$$

If the hypothesis is correct for the selected industries, the β on PE_{high} will be positive for the top 10% of firms, and smaller for the bottom 10%. The top 10% should, therefore, be purchased because they have higher expected returns.

B. P/S Multiple Hypothesis

The next multiple to be investigated is the P/S multiple. It is hypothesized that firms with the lowest P/S multiples will have the largest annual change in stock price, and firms with the highest P/S multiples will have the smallest annual change in stock price. This hypothesis is consistent with O'Shaughnessy's research. This will be tested with the same regressions as the P/E multiple.

For the regression of all industries, the following equation is estimated:

$$\text{Percent change in price} = \alpha + \beta(\text{PS}) \quad (2a)$$

A negative β is expected because the lower the multiple, the higher the returns should be. Thus, low multiples will have a small, negative impact on predicted returns and high multiples will have a large negative impact on predicted returns. When individual industries are examined, the following equation is estimated:

$$\text{Percent change in price} = \alpha + \beta(\text{PS}) + \beta(\text{PSlow}) + \beta(\text{PShigh}) \quad (2b)$$

The bottom 10% of firms, the ones with the lowest P/S multiples, are expected to have the largest β s for PSlow to reflect high returns. The highest 10% of firms, the ones with the highest P/S multiples, are expected to result in the lower β s for PShigh which indicate low returns.

C. P/BV Multiple Hypothesis

Finally, the P/BV multiple will be investigated. It is hypothesized that firms with the lowest P/BV multiple will have the highest annual percent change in stock price, and firms with the highest P/BV multiples will have the lowest annual percent change in

stock price. This hypothesis is consistent with O'Shaughnessy's research of stocks for the 20th century.

The regression with all industries estimates the equation:

$$\text{Percent change in price} = \alpha + \beta(\text{PB}) \quad (3a)$$

According to the hypothesis, a negative β is expected because the lowest β s will predict the highest returns. Low β s will have higher predicted returns, while high β s will reduce returns the most, thus producing the lowest predicted return. The regressions with individual industries estimate the following equation:

$$\text{Percent change in price} = \alpha + \beta(\text{PB}) + \beta(\text{PB}_{\text{low}}) + \beta(\text{PB}_{\text{high}}) \quad (3b)$$

If the hypothesis is correct for the industry specific regressions, the top 10% of firms, determined by a ranking of lowest to highest P/BV multiples per industry, will have the highest annual percent change in stock prices, and the bottom 10% will have the lowest annual percent change in price. Here, PB_{low} will have a high β and PB_{high} will have a low β .

VI. RESULTS

Figures 1 through 3 provide graphs of the relations between multiples and returns. Here, the value of each multiple is plotted against the percent change in price for the entire sample. Figure 1 does this for the P/E multiple. The highest concentration of data points occurs when P/E multiples have values below 500. The graph reveals two trends about the magnitude of multiple values and percent change in price. First, stocks with the lowest P/E multiple values appear to have higher positive returns. There are points in the negative region, but a majority of them are concentrated above the 0% change line. This

can be seen in Figure 1a, which depicts observations with a P/E multiple below 250 and a return below 250%. While a sizable portion of the sample lies below the 0% line, a majority appear to lie above it. Also, the positive returns of low P/E multiples are greater than the negative returns, for the sample depicted. Low P/E multiples appear to be desirable characteristics of stocks. Second, stocks with very high P/E multiples appear to have the lowest returns. A majority of these points appear to be located below the 0% change in price line. High values appear to be undesirable characteristics of stocks.

Figure 2 is the same as Figure 1 for the P/S multiple. The shape is very similar to Figure 1. The majority of sample stocks have P/S values of less than 20. PS values close to zero tend to have the highest percent change in price. The majority of data points with values close to zero appear to be located in positive territory. Figure 2a depicts observations with a P/S multiple value less than or equal to ten and a percent change in price of 250% or less. This figure shows that many observations lie below the 0% change line, but a majority appear to lie above it. Also, the magnitude of positive returns for low multiples appears to exceed the magnitude of negative returns. This suggests that very low values are predictive of higher returns. As the P/S multiples increase towards 20, the concentration of data points decline sharply towards zero percent. Most points beyond 20 are located in negative territory. This suggests that high PS values are not desirable characteristics of stocks.

Figure 3 is the same as Figure 1 and Figure 2, but for the P/BV multiple. Figure 3 has the same general characteristics as the first two. The lowest multiples, those less than 20, are concentrated above zero percent, and have the highest percent changes in price. As the value exceeds 20, the magnitude of the percent change in price declines to a level

around 0%. Figure 3a depicts observations with P/BV multiples of ten and below, as well as returns of 250% or less. Here, a majority of observations appear to lie above the 0% change line. The highest positive returns for these observations are also larger than the lowest negative returns. This suggests that low P/BV multiples could be used to predict higher returns.

A. P/E Multiple Results

Table 2 presents the coefficient estimates for equation (1a) and (1b). The PE β in column 1 represents the average return of a stock from the sample. The PE_{low} and PE_{high} β s are not included in equation (1a) because it examines all stocks, and not specific deciles. The β s for PE, PE_{low}, and PE_{high} are used for all successive columns to estimate equation (1b) for each broad industry. Collectively, they are used to model estimated percent changes in stock prices. For example, the manufacturing β s can be used to create the model:

$$\text{Percent change in price} = 24.9 - .469(\text{PE}) + 3.064(\text{PE}_{\text{low}}) + .438(\text{PE}_{\text{high}})$$

The estimated change in price for stocks with the lowest P/E multiple values is the sum of the PE β and PE_{low} β . If the stock has a PE value in the top decile, the estimated change in price is the sum of the PE β and the PE_{high} β . These are calculated at the bottom of Table 2. Overall, the estimated effects with the variable PE_{low}, indicates higher returns than the PE_{high} variable. This is seen in the regression for all industries, where the PE_{low} coefficient is greater than the PE_{high} coefficient. The regression for all SIC codes resulted with a predicted change of price of .513%. When the sample is disaggregated to seven industries, the PE_{low} variable predicts higher returns, than the PE_{high} variable for

the mining, construction, manufacturing, and wholesale industries. For the remaining industries, agriculture, forest and fishing; transportation; and retail, the PE_{high} variable indicates higher returns than the PE_{low} variable. For these three industries, however, the return is negative. Because the coefficient on PE_{low} was dropped for the agriculture, forestry, and fishing industry, the predicted return for PE_{low} equals the PE coefficient of -.498.

The estimated coefficients vary across industries. Certain industries have β coefficients that are statistically significant. The PE variable is statistically significant for the agriculture, forestry, and fishing; manufacturing; transportation; retail; and wholesale industries. The PE_{low} variable has a statistically significant coefficient for the entire sample and for manufacturing. The PE_{high} variable has a statistically significant coefficient for the agriculture, forestry, and fishing; manufacturing; transportation; wholesale; and retail industry. None of the coefficients for construction are significant. Therefore, these are probably the least reliable. These outcomes may be due to the sample sizes. All industries and manufacturing had the largest sample sizes while construction had one of the smallest samples.

B. P/S Multiple Results

The regression results presented in Table 3 are the β coefficients estimated from equations (2a) and (2b). The PS β in the first column is used to estimate the returns for all stock in the sample. The β s for PS_{low} and PS_{high} are excluded from equation (2a) because it estimates returns for the entire sample and not a specific decile. All three β s are used in equation (2b) to estimate returns for each broad industry. Equation (2b) only

examines stocks with P/S multiples in the top and bottom deciles. If a stock has a multiple in the lowest decile, the estimated return is the sum of the PS β and the PS_{low} β . If a stock has a P/S multiple in the top decile, the estimated return is the sum of the PS and PS_{high} β s. The bottom of Table 3 contains the calculated return estimates. For the regression using all industries, the estimated return is -.108%, using equation (2a). The PS_{low} variable for this regression represents the bottom decile of all stocks. Its coefficient is 150%. It is higher than the PS_{high} coefficient of .176% because the manufacturing industry has a high coefficient of 268.8% and represents over one half of the sample. When the sample is disaggregated into seven broad industries, the PS_{low} variable predicts high positive changes in price for the mining, manufacturing, transportation, wholesale, and retail industries. It predicts negative returns for the agriculture, forestry, and fishing industry and construction. The two industries are the only two where PS_{high} predicts a higher return than PS_{low}. However, the PS_{low} variable was dropped for the regression with agriculture, forestry, and fishing and the coefficient is zero. Therefore, this negative return equals the PE coefficient.

The coefficients for the PS variables are all statistically significant, except for PS_{low} for the agriculture, forestry, and fishing industry and the construction industry.

C. P/BV Multiple Results

The regression results presented in Table 4 are the β coefficients used to estimate equations (3a) and (3b). Equation (3a) estimates the average return of any stock in the sample by using the PB β . Equation (3b) is estimated by using the PB, PB_{low}, and PB_{high} β s. This equation estimates the return on a stock belonging to one of the seven

broad industries. It only examines stocks with P/BV multiples in the top and bottom deciles for each industry. The estimated return for a stock with a P/BV multiple in the bottom decile is the sum of the PB β and the PBlow β . The estimated return for a stock with a P/BV multiple in the top decile is the sum of the PB and PBhigh β s. These are the same models as the PE and PS models described above, and the estimated returns are calculated at the bottom of Table 4. For the regression using all stocks in the sample, the estimated return is -3.46%. The PBlow variable for this regression represents the bottom decile of all stocks. Its coefficient is 17.56%. It is higher than the PBhigh coefficient of 3.44% because the manufacturing industry has a high coefficient of 25.44% and represents over one half of the sample. The PBlow variable predicts a higher change in price for the manufacturing, transportation, and retail industries. The PBhigh variable predicts higher returns for the agriculture, forestry, and fishing; mining; construction; and wholesale industries. Of these, only the construction industry has a positive predicted change in price of 0.16%. Also, the PBlow coefficient was dropped for the agriculture, forestry, and fishing industry. The estimated return for the lowest decile stocks is only based on the PB β .

The coefficients for the regression of all industries and the manufacturing industry are all statistically significant. The PB and the PBhigh variables are statistically significant for the transportation and retail industries, and the mining industry, to a lesser degree. None of the variables are statistically significant for the agriculture, forestry, and fishing and wholesale industry. Only the PBhigh variable is statistically significant for the construction industry.

D. Three-Factor Regression

Table 5 presents the results for the regressions of returns and the seven broad industries. For the P/E multiple, the results are not consistent with the regressions involving only the P/E multiple. Here, the PEhigh variable predicts more favorable returns than PElow for the agriculture, forestry, and fishing; mining; manufacturing; transportation; and wholesale industries. It, however, only predicts a positive return for the agriculture, forestry, and fishing industry. Returns for each individual industry, and the all-industry regression, are close to zero. This is consistent with the previous regression, where all industries, except for mining, manufacturing, and wholesale had estimated returns of less than 1%.

The P/S multiple results are consistent with the previous regressions. The PSlow variable predicts higher returns for the mining, manufacturing, transportation, wholesale, and retail industries. These are the same industries that the PSlow variable predicted higher returns for in the previous regression. Also, the estimated returns have small variations between the two regressions.

The P/BV multiple results are not consistent with the previous regressions. In the regression with only the P/BV multiple, the PBhigh variable predicted higher returns a majority of the time. In this regression, the PBhigh variable also predicts higher returns a majority of the time. It does this for the agriculture, forestry, and fishing; mining; construction; transportation; wholesale; and retail industries. However, the returns are much higher. They range from 19.243% for transportation to 101.827% for construction. There is a negative estimated return for manufacturing, which is lower than the estimated return for PBhigh.

The regression results presented in Table 5 suggest that using all three multiples is more informative than using any individual multiple. This is seen in the R-squared values, which are generally lower in Tables 2 through 4. When all multiples are included in the regressions, in Table 5, the R-squared values increase. This means more of the variance is being explained by. It must be noted that a majority of the variation is explained by the P/S multiple, which consistently has the highest R-squared values. This further supports the hypothesis that the P/S multiple can be used to predict higher returns.

E. Specific-Industry Results

Finally, ten specific industries, defined by their four-digit SIC code, were selected. The selection was made on the basis of the availability of data. All nine of the multiple variables were used for each regression to see how each affected the predicted change in price for a single industry. The results are presented in Table 6. Mining, manufacturing, transportation, retail, and wholesale were selected as the broad industries to choose the sample of ten. These industries were chosen because these broad industries generally had statistically significant coefficients. Two industries were selected for each of these five broad industries. For these industries, the PE_{low} predicted higher percent changes in price, than the PE_{high} variable, for SICs 1040, 2510, 5070, and 5661. The PS_{low} variable predicted higher percent changes in price for SICs 1040, 1311, 3678, 4412, 4899, 5070, 5171, 5661, and 5812. The PB_{high} predicted higher percent changes in price than PB_{low} for SIC 1040, 1311, 2510, 3678, 4412, 5070, 5171, and 5661. Of these, SIC 1040, 1311, 5070, and 5812 have negative estimated returns. Overall, the PS_{low}

variable predicts much higher changes in price than any other variable. For example, with SIC 1311, the PSlow coefficient is 102.7 and is statistically significant.

VII. CONCLUSION:

I examined the relation between price multiples and stock performance using data from 2001 to 2007. I did this by collecting data on multiples and stock returns and regressing the percent changes in price against the top and bottom deciles of price multiples for specific industries. I find evidence that not all multiples are equally informative about returns. I find that the P/E multiple results do not support the hypothesis, but the P/S multiple results do support it. The P/BV multiple results are not easily interpreted and thus no conclusion is drawn.

Overall, the statistical results for the P/E multiple do not support the hypothesis. The results indicate that stocks with low price to earnings multiples tend to have higher returns, and stocks with high price to earnings values tend to have low returns. The PElow variable estimates most returns to be positive, while the PEhigh variable estimates most returns to be negative. The hypothesis was based on the belief that investors are willing to pay higher prices for earnings, when it is believed earnings will grow in the future. It seems more likely that investors would prefer to pay less for earnings, or that the P/E multiple does not capture this belief. There is evidence that the P/E multiple can be used to create a buy or sell strategy. By selecting only stocks with the lowest 10% of price to earnings ratios, an investor may be able to earn positive returns. This, however, appears to be a weak strategy, for the broad-industry level and the specific-industry level, because the predicted returns tend to be low. Most estimated returns are below 5%. Also,

for the ten specific industries examined, the PE_{low} variable only estimates higher returns than PE for four industries. Furthermore, the regression results in Table 5 appear to suggest that PE_{high} indicated higher returns, even though they are low.

The statistical results collected for the P/S multiple supports the hypothesis. The PS_{low} variable estimates mostly positive returns, and PS_{high} estimates mostly negative returns. The PS_{low} variable tends to pick stocks with very high returns. The average return for most broad industries was greater than 90%, while the PS_{high} variable tends to indicate negative returns. This is seen in the regression results reported in Table 3 and Table 5. There is more support when the regression results for the specific-industry level are examined. Five industries have estimated returns greater than 100%, and four of these have statistically significant β coefficients. This provides evidence that the P/S multiple can be used to create a strategy for buying and selling stocks. Many of the β s for the PS_{low} variable are statistically significant, especially for the broad industries. These data are reliable and indicate that high returns can be achieved by buying stocks with low price to sales multiples, as compared to other stocks in a broadly defined industry.

The results for the P/BV multiple do not support the hypothesis. The estimated returns for the PB_{low} variable vary between positive and negative for both broadly defined and specific industries, but it tends to estimate negative returns. The PB_{high} variable also varies: it tends to predict returns that are close to zero for broad industries and varies between positive and negative returns for specific industries. The regressions for broad industries and all variables, presented in Table 5, are not consistent with the aforementioned regressions. They suggest that PB_{high} can indicate high, positive returns. It is not clear if either variable can be used to develop a strategy because of these

variations. Only three β s on the PBlow variable, for the ten specific industry regressions, and none of the β s on the PBhigh variable are statistically significant. Because of the lack of consistency of β s and the lack of statistical significance, the P/BV multiple does not appear to be a sound choice for basing an investment strategy.

VIII. FIGURES AND TABLES

Figure 1
P/E Multiple and Percent Changes in Price

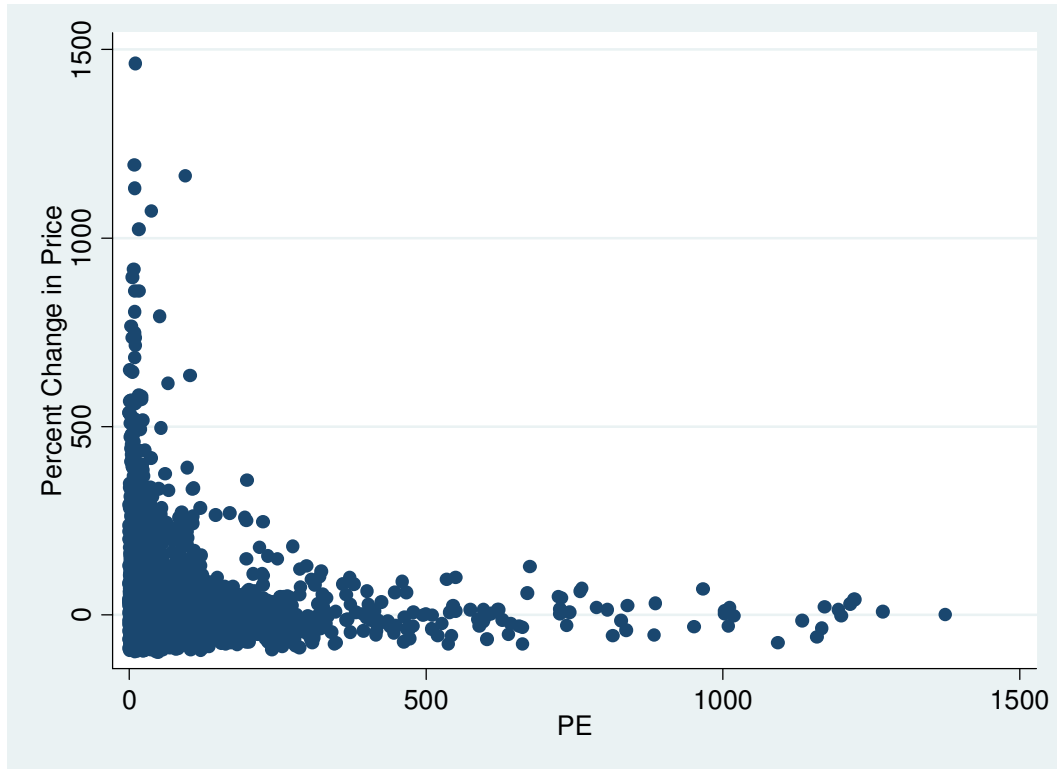


Figure 1a
P/E Multiple and Percent Changes in Price

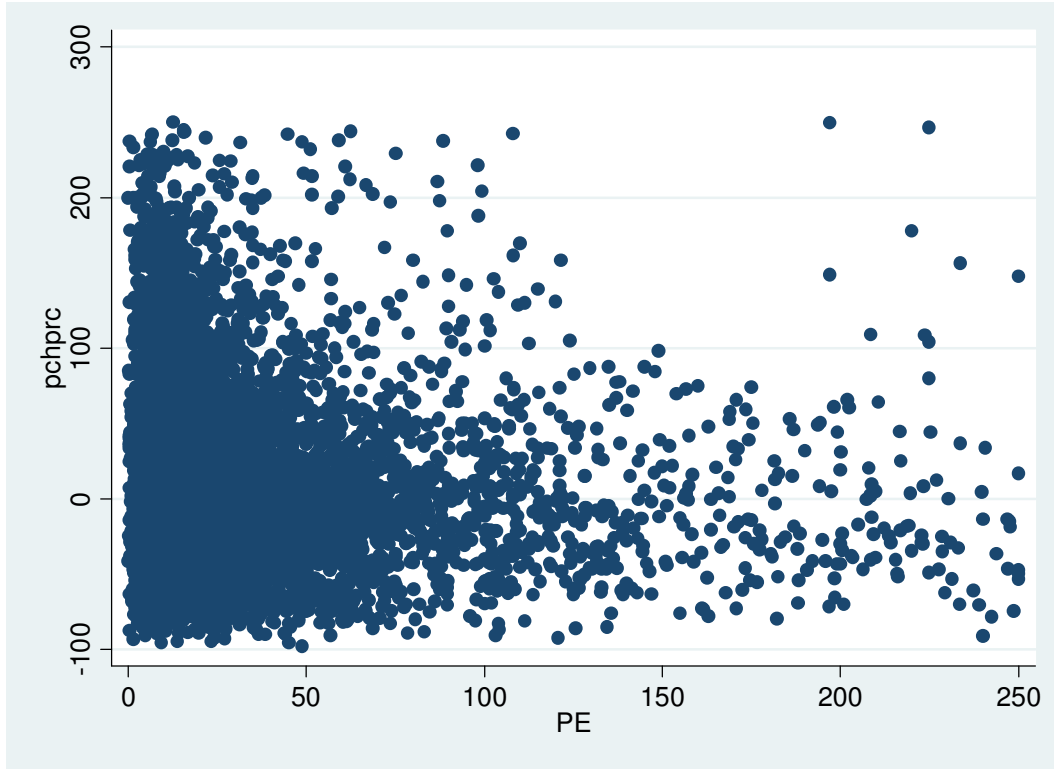


Figure 2
P/S Multiple and Percent Change in Price

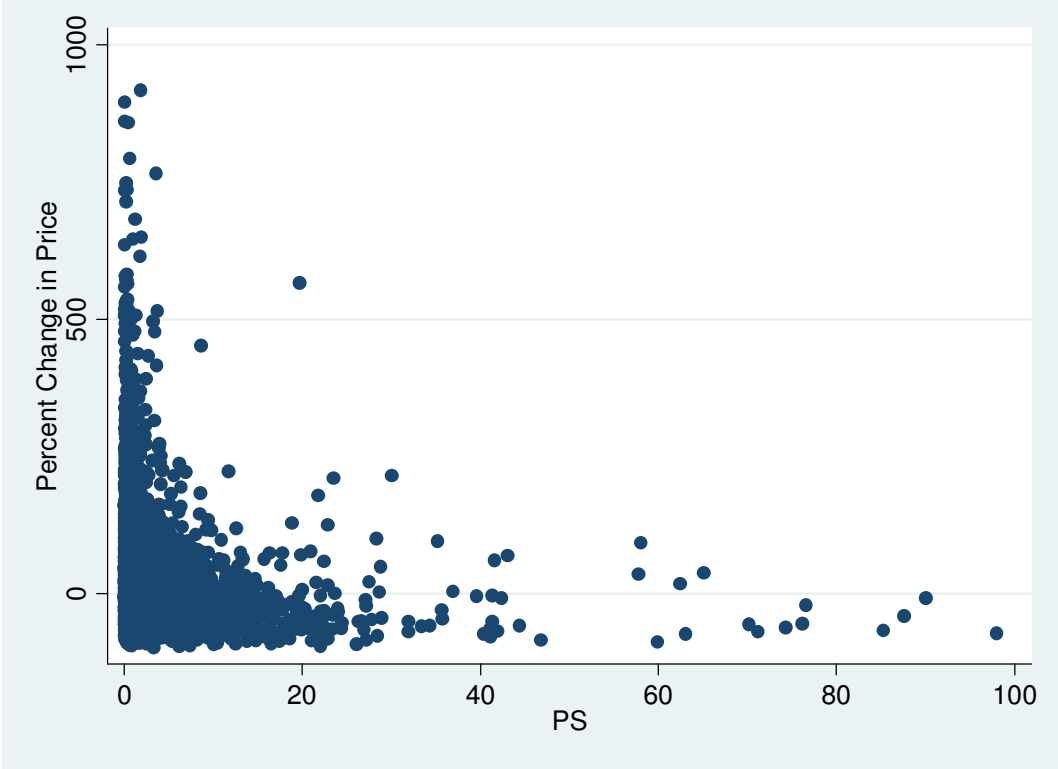


Figure 2a
P/S Multiple and Percent Change in Price

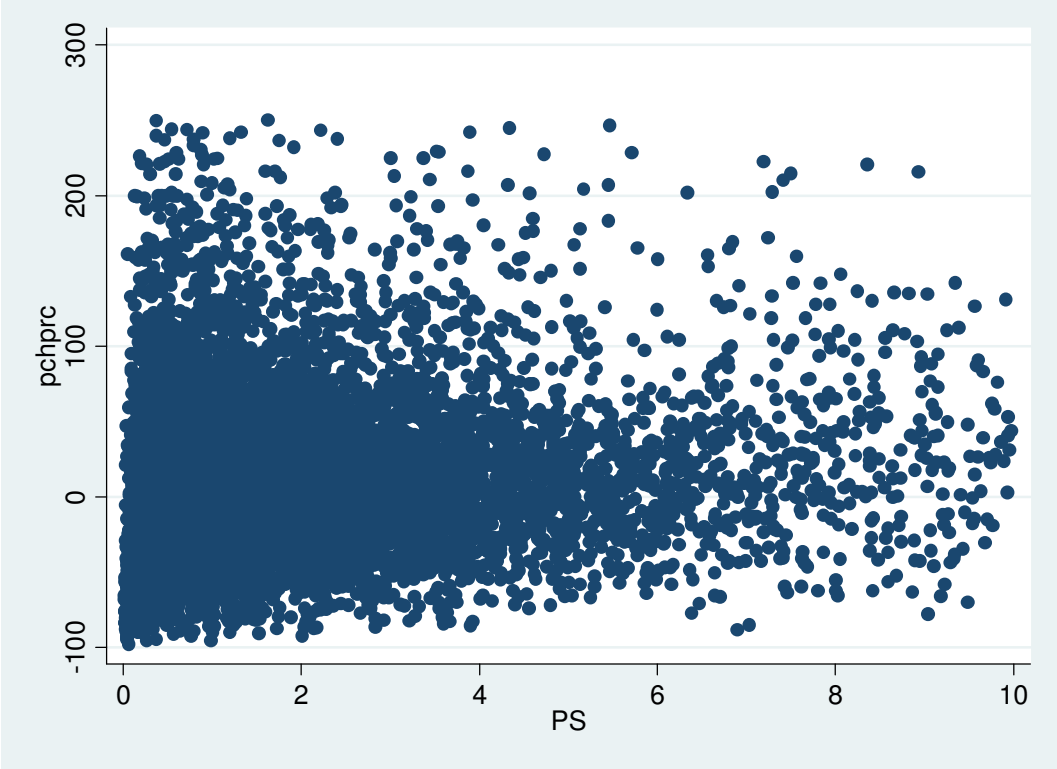


Figure 3
P/BV Multiple and Percent Change in Price

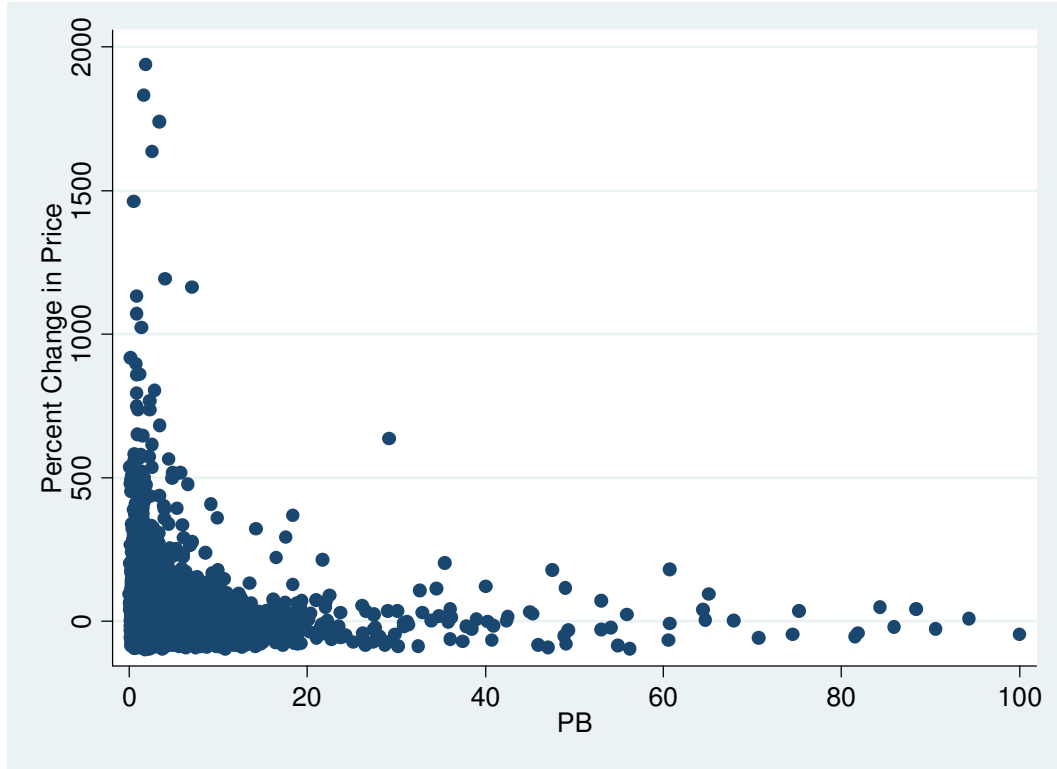


Figure 3a
P/BV Multiple and Percent Change in Price

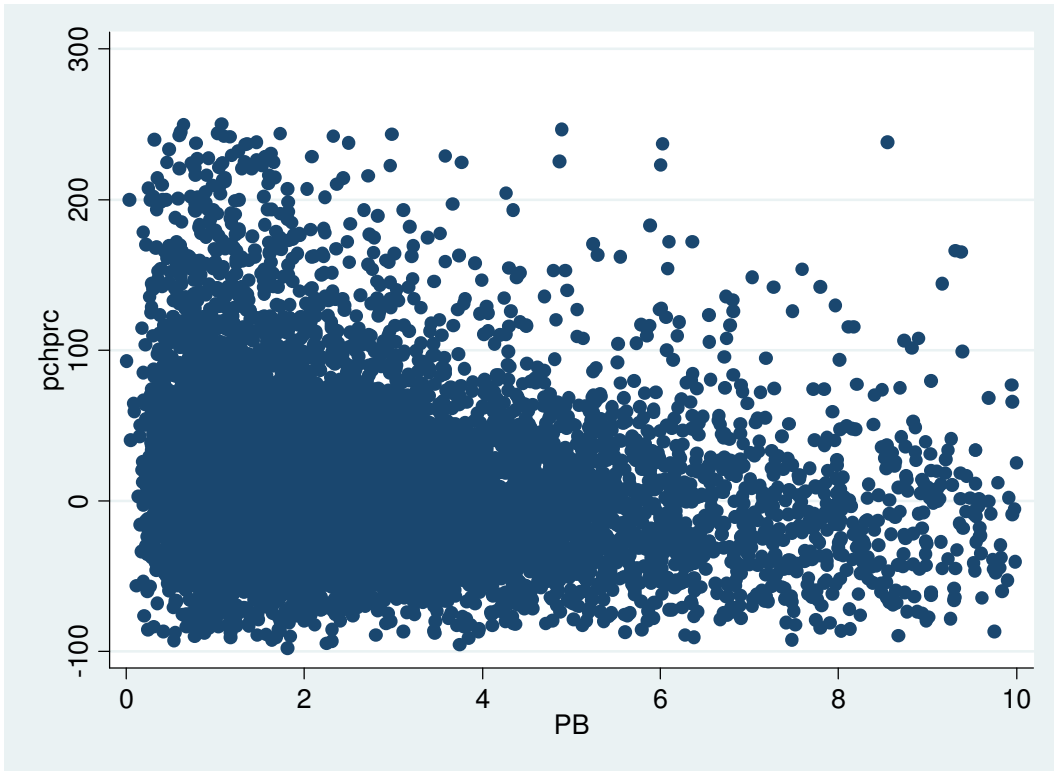


Table 1

Variable	Obs	Mean	Std. Dev.	Min	Max
PE	12324	38.335	134.422	.0169492	6343.75
PElow	12324	0.462	1.805	0	14.21918
PEhigh	12324	20.386	136.342	0	6343.75
PS	12324	6.536	245.076	.0178398	21791.43
PSlow	12324	0.044	0.261	0	15.06468
PShigh	12324	3.840	150.281	0	12509.89
PB	12324	3.505	15.218	.0040063	828.0551
PBlow	12324	0.041	0.181	0	1.588983
PBhigh	12324	1.509	15.294	0	828.0551

Descriptive Statistics

Data Definitions:

PE is the P/E multiple for each stock.

PElow is the P/E multiple for stocks in the lowest decile, based on a ranking of stocks based on the P/E multiple.

PEhigh is the P/E multiple for stocks in the highest decile, based on a ranking of stocks based on the P/E multiple.

PS is the P/S multiple for each stock.

PSlow is the P/S multiple for stocks in the lowest decile, based on a ranking of stocks based on the P/S multiple.

PShigh is the P/S multiple for stocks in the highest decile, based on a ranking of stocks based on the P/S multiple.

PB is the P/BV multiple for each stock.

PBlow is the P/BV multiple for stocks in the lowest decile, based on a ranking of stocks based on the P/BV multiple.

PBhigh is the P/BV multiple for stocks in the highest decile, based on a ranking of stocks based on the P/BV multiple.

Table 2
P/E Regressions

This table represents the results for the regression of: $ret = \alpha + \beta(PE)$ and $ret = \alpha + \beta(PE) + \beta(PE_{low}) + \beta(PE_{high})$

VARIABLES	Industry SIC range	ALL 1-5999	Agriculture, Forestry & Fishing 1-999	Mining 1000-1499	Construction 1500-1799	Manufacturing 2000-3999	Transportation 4000-4999	Wholesale 5000-5199	Retail 5200-5900
PE		-0.027*** (0.0047)	-0.498** (0.241)	-0.515 (0.693)	-1.572 (1.233)	-0.469*** (0.0847)	-0.593*** (0.100)	-0.516** (0.261)	-1.020*** (0.216)
PE _{low}			0 (0)	4.697 (5.371)	2.316 (3.752)	3.064*** (0.626)	0.292 (0.597)	6.428 (4.324)	0.493 (0.863)
PE _{high}			0.489** (0.234)	0.478 (0.670)	1.501 (1.192)	0.438*** (0.0826)	0.576*** (0.0997)	0.517** (0.254)	0.942*** (0.215)
Constant		18.674*** (1.153)	23.84*** (7.596)	46.21** (21.70)	40.03 (24.77)	24.90*** (2.166)	20.24*** (2.550)	21.97*** (5.326)	30.73*** (4.883)
Observations		12324	72	1078	219	7629	1592	610	1124
R-squared		0.007	0.027	0.002	0.010	0.012	0.023	0.021	0.026
Estimated Effects									
PE + PE _{low}		N/A	-.498%	4.182%	.744%	2.595%	-.301%	5.912%	-.527%
PE + PE _{high}		N/A	-.009%	-.037%	-.071%	-.031%	-.017%	.001%	-.078%

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3
PS Regressions

This table represents the results for the regression of: $ret = \alpha + \beta(PS)$ and $ret = \alpha + \beta(PS) + \beta(PSlow) + \beta(PShigh)$

VARIABLES	Industry SIC range	ALL 1-5999	Agriculture, Forestry & Fishing 1-999	Mining 1000-1499	Construction 1500-1799	Manufacturing 2000-3999	Transportation 4000-4999	Wholesale 5000-5199	Retail 5200-5900
PS		0.008*** (0.0137)	-10.49*** (3.497)	-0.262*** (0.0864)	-88.51*** (33.04)	-0.114*** (0.0182)	-4.648*** (1.508)	-16.77*** (2.099)	-9.858** (4.054)
PSlow			0 (0)	93.41*** (16.22)	-20.21 (70.75)	268.6*** (50.90)	95.54*** (22.75)	399.4** (158.4)	246.3*** (62.25)
PShigh			7.784*** (2.019)	0.280*** (0.0900)	54.66*** (15.07)	0.191*** (0.0303)	3.280*** (1.051)	14.15*** (1.578)	9.263*** (2.910)
Constant		17.586 (1.082)	30.95*** (8.855)	25.26*** (8.818)	75.73** (30.76)	6.632*** (1.726)	14.13*** (2.911)	20.78*** (3.536)	16.83*** (3.790)
Observations		12324	72	1078	219	7629	1592	610	1124
R-squared		0.109	0.147	0.052	0.058	0.263	0.175	0.139	0.104
Estimated Effects									
PS + PSlow		N/A	-10.49%	93.148%	-108.72%	268.486%	90.892%	382.63%	236.442%
PS + PShigh		N/A	-2.706%	-.054%	-33.85%	.077%	-1.368%	-2.62%	-.595%

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4
PB Regressions

This table represents the results for the regression of: $ret = \alpha + \beta(PB)$ and $ret = \alpha + \beta(PB) + \beta(PB_{low}) + \beta(PB_{high})$

VARIABLES	Industry SIC range	ALL 1-5999	Agriculture, Forestry & Fishing 1-999	Mining 1000-1499	Construction 1500-1799	Manufacturing 2000-3999	Transportation 4000-4999	Wholesale 5000-5199	Retail 5200-5900
PB		-.039 (0..084)	-6.790 (6.159)	-17.46* (8.917)	-31.93 (19.70)	-2.433*** (0.866)	-5.140*** (1.326)	-3.559 (2.254)	-6.412*** (1.422)
PB _{low}			0 (0)	-19.27 (20.94)	-10.62 (49.27)	25.44*** (7.170)	5.189 (7.182)	-15.61 (11.98)	19.91 (14.40)
PB _{high}			3.943 (4.836)	17.33** (8.830)	32.09* (18.09)	2.356*** (0.856)	4.538*** (1.280)	3.141 (2.147)	6.553*** (1.406)
Constant		17.768 (1.145)	27.29** (11.20)	76.14*** (28.06)	68.05* (40.86)	20.80*** (2.304)	19.62*** (3.109)	23.26*** (5.343)	25.73*** (4.445)
Observations		12324	72	1078	219	7629	1592	610	1124
R-squared		0.004	0.021	0.007	0.031	0.006	0.016	0.004	0.027
Estimated Effects									
PB + PB _{low}		N/A	-6.790%	-36.73%	-42.55%	23.007%	.049%	-19.169%	13.498%
PB + PB _{high}		N/A	-2.847%	-.13%	.16%	-.077%	-.602%	-.418%	.141%

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5

Estimated Results for Three Factors

This table represents the results for the regression: $ret = \alpha + \beta(PE) + \beta(PElow) + \beta(PEhigh) + \beta(PS) + \beta(PSlow) + \beta(PShigh) + \beta(PB) + \beta(PBlow) + \beta(PBhigh)$

Industry	ALL	Agriculture, Forestry & Fishing	Mining	Construction	Manufacturing	Transportation	Wholesale	Retail
VARIABLES SIC range	1-5999	1-999	1000-1499	1500-1799	2000-3999	4000-4999	5000-5199	5200-5900
PE	-0.406*** (0.0863)	0.0113 (0.270)	-0.347 (0.616)	-0.934 (0.771)	-0.359*** (0.0721)	-0.344*** (0.0894)	-0.140 (0.266)	-0.734*** (0.192)
PElow	0.761 (0.505)	0 (0)	-1.711 (3.598)	1.133 (3.278)	0.0205 (0.726)	-0.0511 (0.627)	3.477 (3.469)	-1.175 (0.949)
PEhigh	0.380*** (0.0840)	0.0756 (0.253)	0.306 (0.594)	0.917 (0.750)	0.337*** (0.0708)	0.332*** (0.0888)	0.186 (0.256)	0.681*** (0.192)
NEWPS	-0.106*** (0.0211)	-10.45** (3.991)	-0.226*** (0.0806)	-79.47*** (25.87)	-0.113*** (0.0180)	-4.250*** (1.325)	-16.51*** (2.146)	-8.437** (3.626)
NEWPSlow	148.3*** (24.74)	0 (0)	92.00*** (17.03)	-42.27 (74.29)	272.1*** (53.00)	92.80*** (22.77)	379.0** (152.9)	242.6*** (71.99)
NEWPShigh	0.175*** (0.0354)	7.829*** (2.357)	0.235*** (0.0841)	48.33*** (11.90)	0.190*** (0.0300)	3.011*** (0.923)	13.99*** (1.633)	7.539** (3.080)
PB	-2.218*** (0.757)	-5.187 (6.180)	-14.40* (8.430)	-17.66 (15.40)	-0.946** (0.466)	-3.463*** (1.105)	-1.295 (2.013)	-3.635*** (1.321)
PBlow	-7.475 (5.612)	0 (0)	-17.03 (21.04)	-2.273 (42.44)	-29.70*** (11.12)	-6.577 (7.584)	-32.14* (17.75)	-3.958 (16.20)

PBhigh	2.185*** (0.747)	2.964 (4.473)	14.31* (8.341)	19.18 (14.15)	0.866* (0.465)	3.233*** (1.079)	0.686 (1.967)	3.592*** (1.313)
Constant	23.44*** (3.293)	36.62*** (12.74)	64.64* (39.16)	104.1* (55.19)	17.37*** (2.045)	25.82*** (3.430)	25.08*** (6.744)	36.20*** (6.179)
Observations	12324	72	1078	219	7629	1592	610	1124
R-squared	0.114	0.167	0.057	0.076	0.270	0.190	0.147	0.126
Estimated Effects								
PE + PElow	N/A	0.0113%	-2.058%	0.199%	-0.3385%	-0.3951%	3.337%	-1.909%
PE + PEhigh	N/A	0.0869%	-0.041%	-0.017%	-0.022%	-0.012%	0.046%	-0.053%
PS + PSlow	N/A	-10.45%	91.774%	-121.74%	271.987%	88.55%	362.49%	234.163%
PS + PShigh	N/A	-2.621%	0.009%	-31.14%	0.077%	-1.239%	-2.52%	-0.898%
PB + PBlow	N/A	2.964%	-2.72%	16.907%	-28.834%	-3.344%	-31.454%	-0.366%
PB + PBhigh	N/A	36.62%	47.61%	101.827%	-12.33%	19.243%	-7.06%	32.242%

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6
B Coefficients for all Multiple Variables

This table represents the results for the regression of: $ret = \alpha + \beta(PE) + \beta(PElow) + \beta(PEhigh) + \beta(PS) + \beta(PSlow) + \beta(PShigh) + \beta(PB) + \beta(PBlow) + \beta(PBhigh)$

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
VARIABLES	Industry SIC	All 1-5999	Mining 1040	Mining 1311	Manu. 2510	Manu. 3678	Trans. 4412	Trans. 4899	Retail 5070	Retail 5171	Wholesale 5661	Wholesale 5812
PE		-0.406*** -0.0863	0.132 (0.245)	-0.710 (1.316)	-2.143 (1.446)	0.562 (0.337)	0.434 (1.055)	-0.771** (0.328)	-2.247 (3.023)	-11.41*** (1.625)	-1.105 (1.838)	-0.641** (0.294)
PElow		0.761 -0.505	2.747 (6.290)	-1.497 (5.185)	4.327 (5.518)	-2.393 (3.998)	-0.462 (4.958)	-1.479 (1.783)	12.59 (13.04)	0 (0)	2.729 (2.507)	-0.935 (1.044)
PEhigh		0.380*** -0.084	-0.188 (0.225)	0.662 (1.288)	1.961 (1.384)	0.884*** (0.203)	-0.394 (1.034)	0.750** (0.326)	0 (0)	10.19*** (1.110)	0.332 (1.433)	0.612** (0.283)
PS		-0.106*** -0.0211	-0.392* (0.202)	-2.512** (1.179)	-68.55** (31.76)	-19.82 (14.10)	-28.51*** (8.686)	-1.464*** (0.388)	97.42 (114.4)	42.66** (9.291)	-81.76*** (28.83)	-4.094 (3.241)
PSlow		148.3*** -24.74	29.27 (26.07)	102.7*** (18.58)	-148.8 (105.9)	752.3*** (130.6)	54.06** (22.67)	22.70* (12.72)	226.8 (154.2)	0 (0)	101.8* (58.06)	368.8*** (121.7)
PShigh		0.175*** -0.0354	0.487* (0.257)	1.242** (0.513)	-8.559 (19.41)	0 (0)	12.52*** (3.586)	1.102*** (0.266)	0 (0)	-28.29** (8.095)	0 (0)	4.551 (7.077)

PB	-2.218*** -0.757	-11.98* (6.082)	-38.66 (27.28)	6.068 (8.975)	-9.474 (6.534)	15.02 (17.26)	0.543 (5.222)	-34.26 (22.65)	-46.01** (8.222)	3.939 (14.38)	-1.843 (2.032)
PBlow	-7.475 -5.612	-50.33* (29.06)	-44.20 (42.01)	-1.832 (10.93)	-102.3 (107.0)	-26.13 (53.93)	43.74 (49.67)	-309.5* (156.8)	-43.63** (13.50)	-18.63 (52.75)	40.86 (36.02)
PBhigh	2.185*** -0.747	4.779 (3.665)	33.81 (22.42)	6.306 (5.302)	9.548 (6.097)	1.378 (11.12)	-2.640 (4.674)	30.71 (21.27)	9.320 (6.056)	0 (0)	1.704 (2.020)
Constant	23.44*** -3.293	65.14*** (21.35)	136.2 (96.85)	63.46* (31.26)	36.36 (45.00)	67.36** (25.92)	21.69 (15.67)	62.92 (36.48)	264.7*** (13.11)	53.44 (53.96)	26.15*** (7.546)
Observations	12324	87	664	36	35	112	63	25	11	33	307
R-squared	0.114	0.135	0.070	0.434	0.642	0.219	0.195	0.319	0.980	0.315	0.349
Estimated Effects											
PE + PElow	N/A	2.879%	-2.207%	2.184%	-1.831%	-0.028%	-2.25%	10.343%	-11.41%	1.624%	-1.576%
PE + PEhigh	N/A	-0.056%	-0.048%	-0.182%	1.446%	0.04%	-0.021%	-2.247%	-1.22%	-0.773%	-0.029%
PS + PSlow	N/A	28.878%	100.185%	-217.35%	732.48%	25.55%	21.236%	324.22%	42.66%	20.04%	364.706%
PS + PShigh	N/A	0.095%	-1.27%	-77.109%	-19.82%	-15.99%	-0.362%	97.42%	14.37%	-81.76%	0.457%
PB + PBlow	N/A	-62.31%	-82.86%	4.236%	-111.774%	-11.11%	44.283%	-343.76%	-89.64%	-14.691%	39.017%
PB + PBhigh	N/A	-7.201%	-4.85%	12.374%	0.074%	16.398%	-2.097%	-3.55%	-36.69%	3.939%	-0.139%

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes:

- (1) Gold and Silver Ores
- (2) Crude Petroleum and Natural Gas
- (3) Household Furniture
- (4) Electronic Connectors
- (5) Deep Sea Foreign Transportation of Freight
- (6) Communications Services, NEC
- (7) Wholesale – Hardware and Plumbing and Heating Equipment and Supplies
- (8) Wholesale – Petroleum Bulk Stations and Terminals
- (9) Retail – Show Stores
- (10) Retail – Eating Places

IX. REFERENCES

Dorsey, Pat. The Five Rules for Successful Investing. Hoboken, NJ: John Wiley & Sons, Inc., 2004.

Durell, Philip. "How to Use the P/B Ratio." The Motley Fool. Oct. 13, 2005.

<http://www.fool.com/investing/value/2005/10/13/how-to-use-the-pb-ratio.aspx>
(27 March 2009).

English, James. Applied Equity Analysis. New York: McGraw-Hill Companies, Inc., 2001.

Matras, Kevin. "Price Targets and Multiple Expansion." Zacks. Oct. 23, 2007.

<http://www.zacks.com/newsroom/commentary/index.php?id=6179>. (10 April 2009).

O'Shaughnessy, James. What Works on Wall Street. New York: McGraw-Hill, 1998.

Reese, John. "Super Stocks for Ken Fisher Fans." Forbes. Mar. 11, 2008.

http://www.forbes.com/2008/03/11/conoco-marathon-fisher-pf-ii-in_jr_0311guruscreen_inl.html (27 March 2009).

Thomsett, Michael. The Mathematics of Investing. New York: John Wiley & Sons, Inc., 1989.