Th Decline in the P/E Ratio Effect

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Abstract

The P/E ratio effect is the tendency for low P/E portfolios to outperform high P/E portfolios. Historically this has been true by a significant margin regardless of utilizing a market average or an industry average to define what is considered low or high. However, between 1999-2019 this outperformance greatly declined. In the period of 2000-2009 low P/E portfolios on average outperformed their high ratio counterparts by .8% to 2.2% on a monthly basis. By 2019, this outperformance declined to near zero. When applying the four factor Carhart model to the portfolios, the decline in the P/E effect can largely be explained by the decline in the significance of the HML factor and a stronger association between low P/E portfolios and large cap portfolios represented by the SML factor. This may be an indication of markets becoming more efficient, assuming P/E ratios are a weak proxy for risks.

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Part I: Introduction

In the book *Security Analysis* first published in 1934, renowned value investors Benjamin Graham and David Dodd became some of the first to popularize the notion of using price to earnings (P/E) ratios in order to gauge how under or overvalued a security was. Securities with relatively low P/E ratios were considered undervalued and would lead to higher returns than those with high P/E ratios. This became known as the P/E effect. In large part due to the ratio being simple and straightforward, it has become the most widely known metric for security valuation among both professional and amateur investors.

There could be several reasons why a securities' P/E ratio may be low. If the firm is expected to have poor earnings performance in the future, a low P/E ratio is seen as justified. But if its earnings are to maintain moderate growth, its low P/E ratio may be the markets overlooking it and undervaluing the security. Likewise, a security with a high P/E ratio may be justified if the firm's future earnings are growing at a relatively high rate.

Since the 1960s, there has been a substantial amount of academic literature written on the relationship between P/E ratios to future returns and the existence of a P/E effect. Nicholson (1960) had shown that low P/E stocks consistently outperformed between 1937-1954. Breen (1967) showed portfolios constructed with low P/E ratios relative to the market average or industry average both outperformed randomly constructed portfolios.

These finding contradict assertions made by other papers at the time which found strong evidence an efficient market. The capital asset pricing model (CAPM) developed by William Sharpe (1964) and then further elaborated by Lintner (1965) showed the relationship between a security's relative market risk or market beta and its expected return. Research by Fama (1970) asserted capital markets are efficient and security prices fully reflect all available current information. This directly implies consistently abnormal risk adjusted returns should not exist.

However, using 1957-1971 data Basu (1977) found when comparing low and high P/E portfolios, low P/E portfolios outperformed even after adjusting for risk. Peavy and Goodman went further and when controlling for non-P/E related factors like firm size, industry effects, and infrequent trading found low P/E stocks provided "clearly superior risk-adjusted returns" (Peavy & Goodman, 1983, p.43). Market anomalies like this and the existence of money managers such as Warren Buffet who have consistently been able to achieve higher than expected risk adjusted returns suggest there are other factors than market beta that help explain the variance of returns among different portfolios.

Fama and French (1993) built upon the single factor CAPM model by adding High Minus Low (HML) and Small Minus Big (SMB) factors. The Fama-French 3-factor model explained more than 90% of return variation for portfolios. The extra two factors accounted for the historical tendency of smaller firms to outperform larger ones and for firms with a high book to market ratio to outperform firms with a low book to market ratio. Whether or not these tendencies represent market anomalies remains up for debate. If markets are efficient, higher returns should be associated with higher risk. HML and SMB could be representing default and liquidity risk, respectively.

Other subsequent papers have sought to add factors to the Fama-French model resulting in 4, 5, or even 7 factors. The Carhart model (Carhart 1997) added a fourth factor momentum to capture the tendency of security to continue to rise if it is increasing and its tendency to fall if it is decreasing.

However, none of these factor models directly considered the historical tendency for low P/E ratio securities to outperform their high P/E ratio counterparts. One potential explanation could be low P/E portfolios are susceptible to more risks. If the low P/E portfolios are not associated with higher risks of any kind compared to their high P/E counterparts this would suggest financial markets are not as efficient as some propose. The following paper seeks to determine whether portfolios based on low P/E ratio securities have outperformed portfolios with higher P/E securities between 1999-2019, and determine if the difference in portfolio returns can be explained by risk factors like variability of returns or factors that make up the Carhart model.

Part II: Methodology

Measuring The P/E Effect

Defined below are the two most used P/E ratios: 12 months trailing, and 12 months forward. For simplicity, this paper will now refer to P/E 12 month trailing as PE, P/E 12 month forward as FPE, and P/E when referring to both measures.

$$PE = \frac{Current\ Price}{12\ Month\ Trailing\ Earnings\ Per\ Share} \tag{1}$$

$$FPE = \frac{Current\ Price}{12\ Month\ Forward\ Earnings\ Per\ Share} \tag{2}$$

While both ratios typically lead to similar relative valuations when implemented, they can differ substantially when applied to firms with relatively high earnings growth. Firm A may have a higher PE than firm B, but a lower FPE due to it having a higher growth rate. In practice, FPE is purely based on forward looking earnings estimates while PE is based on largely known reported earnings. Ideally a rolling 12-month forward earnings estimate for each security would have been used to calculate FPE. However, the data on historical earnings estimates is very limited. Instead this paper uses actual reported earnings, with the assumption that they reflect expected 12-month forward and 12-month trailing earnings for the times.

In a similar fashion to Breen 1967, when evaluating whether a security's PE or FPE ratio is relatively high or low, this paper uses both market comparison and industry classification comparison.

Each security has been categorized on four levels based on sub-industry, industry, industry group, and sector. The characterization of these securities is defined by the Global Industry Classification Standard (GICS). Developed by MSCI/Barra and Standard & Poor's in 1999, the GICS has become the most widely used hierarchical industry taxonomy. A key aspect of the GICS is its evolving structure over time. As business environments develop, past characterization may no longer become relevant. The need for new industry or even sector classification may become necessary. The GICS structure has been changed several times since its inception. In its most recent format developed in 2018, there were 11 sectors, 24 industry groups, 69 industries, and 158 subindustries. This is in contrast with its original structure that consisted of 10 sectors, 23 industry groups, 59 industries, and 123 sub industries. Due to classifications being discontinued or reclassified the total number of classifications differs from the latest structural update as seen below in Table 1.

Table 1: Total Classifications Used

Classification	Total Unique Classifications
Sector	11
Industry Group	26
Industry	76
Sub-Industry	192

[1] Table 1 includes all GICS classifications that existed between 1999-2019 and is not limited to those that have been discontinued.

Figure 1: 2018 GICS Structure

To compare the performance of high and low PE/FPE securities, 20 portfolios were created based on relative PE or FPE ratio compared to the median of their respective classifications and the market. For example, if stock A has a PE ratio greater than the market median but lower than its subindustry median then it would be added to the PEHighM and the PELowSI portfolios. The median statistic was used over mean, due to its robust nature and occurrence of companies to have abnormally high P/E ratios when they report abnormally low earnings.

[2] Figure 1 shows the most recent GICS structure and is directly sourced from https://www.msci.com/gics.

Table 2: Portfolios Created

Classification	PE_High	PE_Low	FPE_High	FPE_Low
Market	PEHighM	PELowM	FPEHighM	FPELowM
Sector	PEHighS	PEHLowS	FPEHighS	FPEHLowS
Industry Group	PEHighG	PELowG	FPEHighG	FPELowG
Industry	PEHighI	PELowI	FPEHighI	FPELowI
Sub-Industry	PEHighSI	PELowSI	FPEHighSI	FPELowSI

These portfolios were constructed through an equally weighted method with monthly rebalancing to capture the average effect P/E ratios may have on performance. Certain securities often switched between high and low ratio portfolios as they have short periods of high returns. A key aspect of this paper is to examine the difference between the low/high portfolios for each ratio and classification between 1999 and 2019 (Table 3).

Table 3: Low P/E Portfolio Returns Minus High P/E Portfolio Returns

Classification	PE Low Minus High	FPE Low Minus High
Market	PE_LMH_M	FPE_LMH_M
Sector	PE_LMH_S	FPE_LMH_S
Industry Group	PE_LMH_G	FPE_LMH_G
Industry	PE_LMH_I	FPE_LMH_I
Sub-Industry	PE_LMH_SI	FPE_LMH_SI

If the mean difference of the low/high portfolios is significantly higher than 0, then the paper would conclude that on average the PE/FPE ratio has influenced future performance of securities between 1999-2019.

[3] Table 2 shows the names of the portfolios created. These were used as a basis for comparison. Table 3 shows the variables created to measure the P/E effect by ratio and classification type.

In addition to testing the average difference throughout the entire period, this paper also investigated potential changes in the relationship over time. Baek and Lee 2018 provided evidence of structural breakpoints when comparing long-term market returns to the aggregate market PE ratio. To consider potential structural breaks in the relationships between high and low ratio portfolios, this paper graphically observed the difference in portfolio returns and calculated the mean difference of the structurally different time periods.

Explanations for the P/E Effect

To determine whether the difference in returns can be explained by variability of returns, the historical Sharpe ratio of each low P/E portfolio for each relevant time-period was calculated and compared with its respective high P/E portfolio. The historic Sharpe ratio measures a portfolio's *reward-to-variability* by comparing its arithmetic mean excess risk return for a period to its standard deviation. (Sharpe 1975).

$$Sharpe = \frac{mean(1mr - rf)}{SD(1mr)} \tag{3}$$

If the P/E effect existed after adjusting for risk, then the low P/E portfolios should have a significantly larger Sharpe ratio than their high P/E portfolio counterpart. Likewise, if risk is the primary reason behind the P/E effect, the Sharpe ratios for low and high portfolios should be near the same.

The Carhart model was also applied to the portfolios to explain the difference in returns. The Carhart model is comprised of four factors: excess risk market return (MKTRF), small capitalization security returns minus big capitalization returns (SMB), high book to market ratio (B/M) security returns minus low B/M security returns (HML), and a momentum factor (MOM) which is the difference in returns between securities with high past returns and securities with low past returns.

Using the model below, a linear regression was conducted on the four factors for each of the portfolio's excess risk-free returns. The regressions were conducted for each necessary time period that showed signs of a structural shift.

$$\mathrm{PortExR} = \beta_1 * \mathrm{MKTRF} + \beta_2 * \mathrm{SMB} + \beta_3 * \mathrm{HML} + \beta_4 * \mathrm{MOM} + \alpha + \epsilon \qquad (4)$$

$$PortExR = Portfolio\ Return - Risk\ Free\ Rate \qquad (5)$$

The resulting p-values and adjusted r-squares were then examined and compared between portfolios and time periods. The coefficients with p-values less than .05 were then used explain the P/E effect.

[4] Equation 4 details the regression used upon the data. α represents the intercept.
ϵ represents error or residual. Risk free rate is defined as the rate on the 1-month US treasury bill.

Part III: Data

Securities Data

All available U.S securities that existed within the period of “1999-07-31” to “2019-07-31” were collected from an integrated Compustat-Capital IQ data base accessed from Wharton Data Business Services (WRDS). To be used in this paper five criteria must be met for each security. First, the security must be the primary class of shares for a firm. Second, the security’s fundamental financial reports must be available with no breaks in between while it is publicly trading. Third, the firm of the security must be legally registered in the United States of America. Fourth, the security must have a market capitalization of at least $50 million. Lastly, the security must not have a negative PE or FPE ratio.

The security’s fundamental financial reports requirement refers to having constant quarterly reports on a security’s financials while it is a public trading company. However, this requirement does not limit securities with a consistent partial record. If, for example, a security has consistent reports for 2005 onward but none for quarters prior to 2005, the observations for 2005 onward have been be included. Additionally, this requirement does not extend to securities that have gaps in their reports due to periods of bankruptcy or privatization.

This paper defines market capitalization as the product of common shares outstanding issued monthly and the end of the month price.

$$MarketCapitalization = SharesOutstandingMonthly * EndOfMonthPrice \tag{5}$$

The market capitalization requirement for this paper does not need to be consistent over time. If, for example, a security has a market capitalization of $60 million for the month of January but $49 million for the month of February, the January data point will be included while the February data point excluded.

Like the market capitalization requirement, the non-negative P/E ratio requirement does not need to be consistent over time. If a security has negative PE and FPE ratios for one year and positive ratios two years later, the security will be included in the later dates.

Figures 2 and 3 show the number of securities that meet all requirements compared to the total number of US securities trading. Of the 14,538 securities in the Compustat-Capital IQ database that existed during the selected time period within the US, 4,429 met the requirements. Figures 4 and 5 show the market capitalization of these securities compared to the total US market capitalization. Among the securities that meet the requirements, the data set has a total market capitalization of $27.95 trillion and $9.07 trillion for the latest and earliest date, respectively.

[5] All data was downloaded as a csv file from the WRDS website and edited using R studio.

Figure 2: Number of Securities Used vs Total US Securities Trading 1999-2019

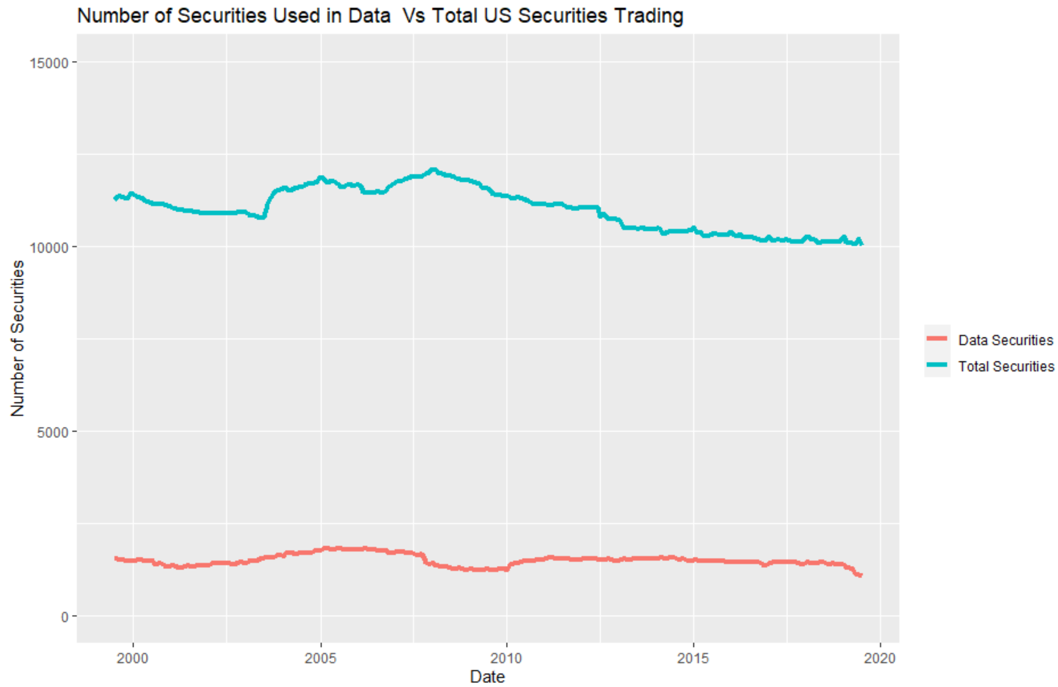
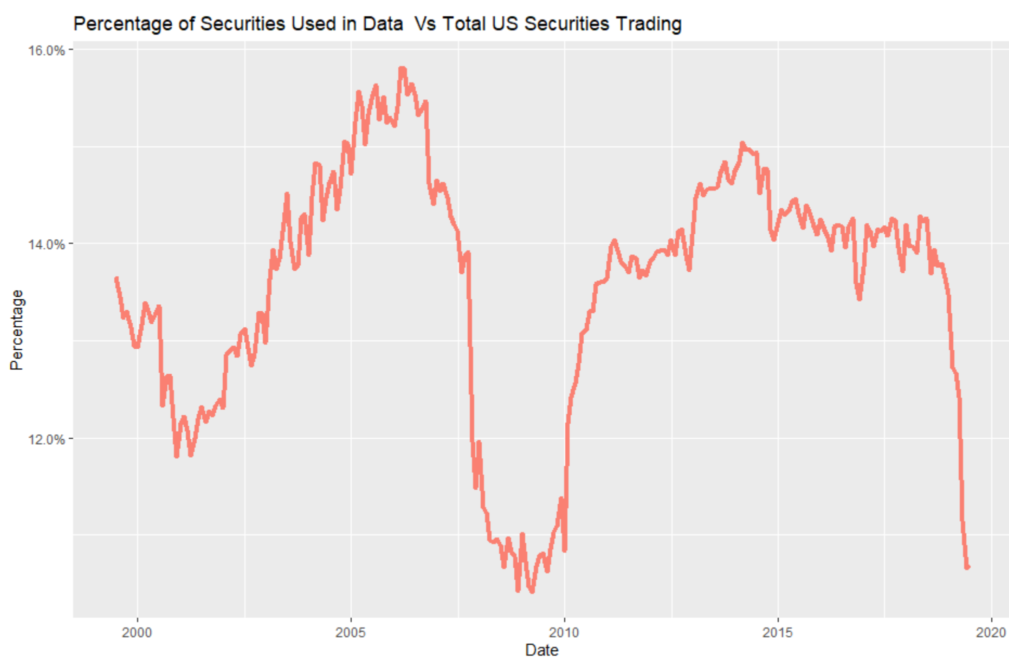


Figure 3: Percentage of Securities Used vs Total US Securities Trading 1999-2019



[6] The large difference in securities shown in Figure 2 is primarily due to very low market cap firms that did not meet the set requirements.

Figure 4: Market Capitalization of Data vs Total US Market Capitalization

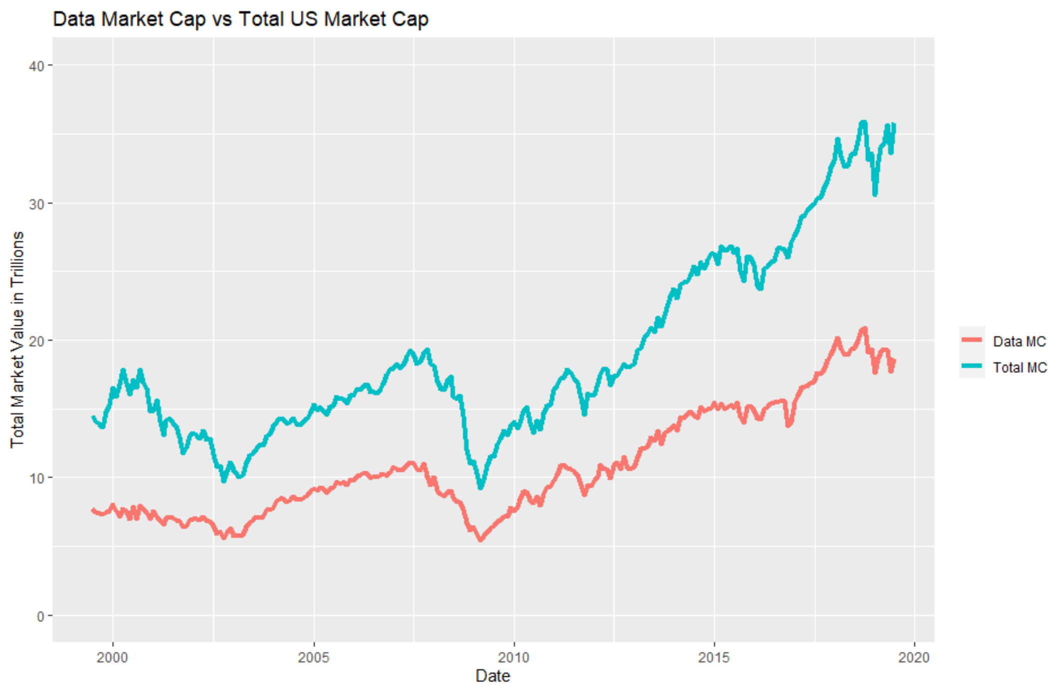
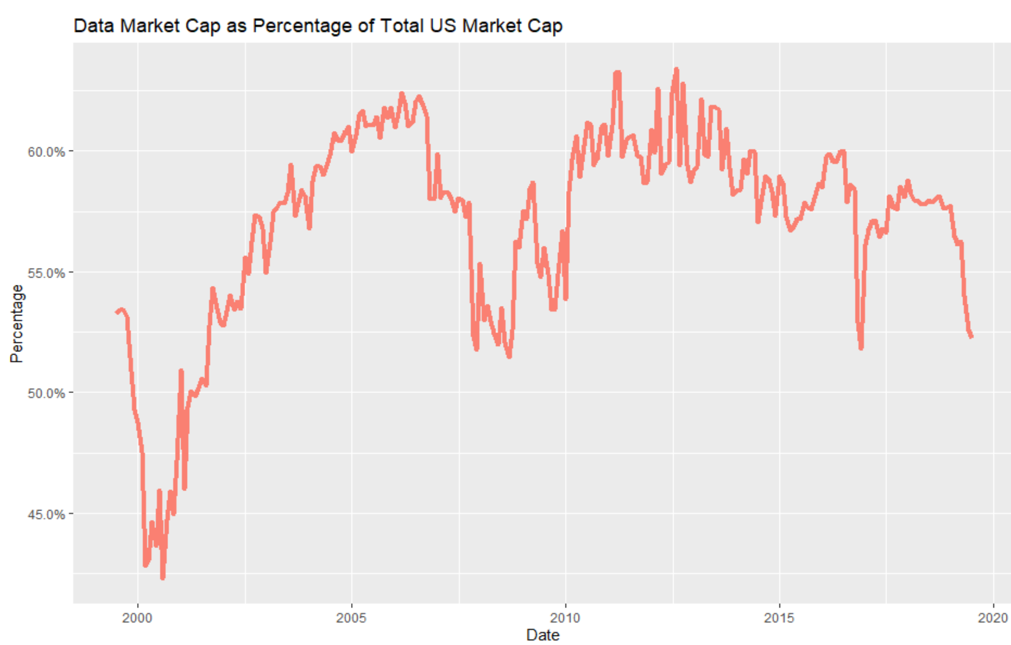


Figure 5: Market Capitalization Data as a Percentage of Total US Market Capitalization



[7] The total market capitalization uses all secruities from the US Computstat-IQ database inlcuding those that do not meet the requirements.

Raw end of the month prices were obtained and properly adjusted for stock splits over time. Monthly price returns (MPR) were then created by calculating the percent increase or decrease of the adjusted security prices from their previous month. Annual dividend yields (DY) were also obtained for their corresponding monthly prices. These yields were adjusted for a monthly basis and then combined with the price returns to form the total monthly returns (TMR).

$$TMR = (MPR + 1) * (DY + 1)^{\frac{1}{12}} - 1 \tag{6}$$

In addition to monthly returns, 1-month future price returns (FMPR) were also created by calculating the percent increase security prices from their next month. In a similar fashion to TMR, these returns were also adjusted to include uniform distribution of dividends across months to calculate total future monthly returns (FTMR). These returns were then used as a basis in measuring performance.

$$FTMR = (FMPR + 1) * (DY + 1)^{\frac{1}{12}} - 1 \tag{7}$$

Of the securities that met the first three requirements, their quarterly diluted earnings per share (EPS) excluding extraordinary items were obtained through the Compustat-Capital IQ database. Diluted EPS is used over basic EPS to reflect the value earned per common share once all convertible securities are considered. Extraordinary items were not included due to their prevalence to distort relative valuation measures like P/E ratios. As with raw prices, EPS data was also adjusted for stock splits over time.

A 12-month trailing, and forward EPS was calculated using a timeframe based proportional linear model for observations that did not correspond to the end of a quarter. If an observation was halfway into Q4, to calculate trailing 12-month EPS, the model took the sum of Q1-Q3, 50% of Q4 from that fiscal year, and 50% from Q4 of the prior fiscal year. These trailing and forward EPS figures were then used in conjunction with adjusted monthly prices to calculate PE and FPE for each month of each security.

For each unique date within the dataset, the median PE and FPE of the market and each value within the 4 classifications was calculated. Afterwards 10 binary variables were created to classify an observation's valuation ratio relationship to that of the median classification ratio. If an observation's ratio was less than the classification's median ratio, the binary variable was assigned a 0, and assigned a 1 if greater than. These binary variables were used to assign which observations went to high or low portfolio of their respective ratio and classification.

Table 4: Binary Relationship to Classification Median Ratio Variables

Classification	PE	FPE
Market	PE_M_Bin	FPE_M_Bin
Sector	PE_S_Bin	FPE_S_Bin
Industry Group	PE_G_Bin	FPE_G_Bin
Industry	PE_I_Bin	FPE_I_Bin
Sub-Industry	PE_SI_Bin	FPE_SI_Bin

For each date, the mean FTMR was calculated using all of the securities within each portfolio to create the equally weighted portfolio 1-month future return. This was then used as the basis for comparing high and low ratio portfolios returns.

Carhart Model Data

Data for the factors that make up the Carhart model were obtained through WRDS from their Fama-French & Liquidity Factors database sourced from Dr. French's Dartmouth website.

MKTRF is the return of a value weighted index of all US stocks including dividends and capital gains minus the US one-month T-bill rate. This includes all securities from figure 2 and figure 3.

$$MKTRF = Market\ Return - US\ 1\ Month\ Tbill\ Rate \tag{8}$$

To construct the SMB and HML factors, French sorted the securities into two market cap and three B/M groups. Large cap securities are those in the top 90%, and small cap securities are those in the bottom 10%. High B/M securities were defined as those being within the top 30% and low B/M securities were defined as those being within the bottom 30%. The independent 2x3 sorts on size and B/M produce six value-weight portfolios, SG, SN, SV, BG, BN, and BV, where S and B indicate small or big and G, N, and V indicate growth (low B/M), neutral, and value (high B/M). French then calculated the SMB and HML factors on a monthly basis using the following definitions.

SMB is the equal-weight average of the returns on the three small stock portfolios for the US minus the average of the returns on the three big stock portfolios.

$$SMB = \frac{1}{3} * (SmallValue + SmallNeutral + SmallGrowth) - \frac{1}{3} * (BigValue + Bigneutral + SmallGrowth) \quad (9)$$

HML is the equal-weight average of the returns for the two-high book to market (B/M) portfolios for a region minus the average of the returns for the two low B/M portfolios.

$$HML = \frac{1}{2} * (SmallValue + BigValue) - \frac{1}{2} * (SmallGrowth + BigGrowth) \quad (10)$$

In a similar fashion to constructing the SMB and HML factors, French used six value-weighted portfolios formed on size and prior (2-12) returns to construct MOM. The portfolios, which were formed monthly, are the intersections of 2 portfolios formed on size (market equity, ME) and 3 portfolios formed on prior (2-12) return. The monthly size breakpoint is the median NYSE market equity. The monthly prior (2-12) return breakpoints are the top 30% and bottom 30%.

MOM is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios.

$$MOM = \frac{1}{2} * (Small\text{High} + BigHigh) - \frac{1}{2} * (SmallLow + BigLow) \quad (11)$$

[8] Equation 8-11 and factor descriptions are directly sourced from Dr. French’s website listed in the bibliography.

Part IV: Results

Measuring the P/E Effect

Tables 5 and 6 below shows the mean 1-month future returns of each portfolio, its standard deviation, and its historic Sharpe ratio for the 1999-2019 time period. For both PE and FPE based portfolios the low ratio portfolios have on average outperformed their high ratio counterpart regardless of classification used. The low PE portfolios monthly returns outperformed by .8%-1%, and low FPE portfolios outperformed by 2%-2.2%. There is only a slight difference between classification used to define high or low ratio securities. Low ratio portfolios based on the market median, outperformed their high ratio equivalents only slightly less then portfolios based sub-industry classifications. The greater performance of low FPE ratios compared to low PE ratios was expected. As mentioned in the methodology section, this paper uses actual information rather than past expected information. Since 12-month forward earnings estimates are much less accurate than 12-month trailing earnings estimates, the higher returns for low FPE portfolios are likely the result of markets adjusting to new information.

Financial literature would suggest higher returns would require higher risk. This is not the case here. The standard deviation of the low ratio portfolios is only slightly greater than if not equal to their high ratio counterparts. What is more, the historic Sharpe ratio is significantly greater for the low ratio portfolios compared to their high counterparts, indicating that even after adjusting for risk low P/E portfolios outperformed high P/E portfolios between 1999 and 2019.

Table 5: PE Portfolio Stats

Portfolio	Mean	SD	Sharpe
PEHighM	0.01040	0.04426	0.23494
PELowM	0.01836	0.04517	0.40645
PEHighS	0.00953	0.04295	0.22178
PELowS	0.01927	0.04583	0.42061
PEHighI	0.00919	0.04321	0.21273
PELowI	0.01973	0.04549	0.43381
PEHighG	0.00927	0.04319	0.21454
PELowG	0.01951	0.04548	0.42908
PEHighSI	0.00944	0.04350	0.21708
PELowSI	0.01958	0.04494	0.43576

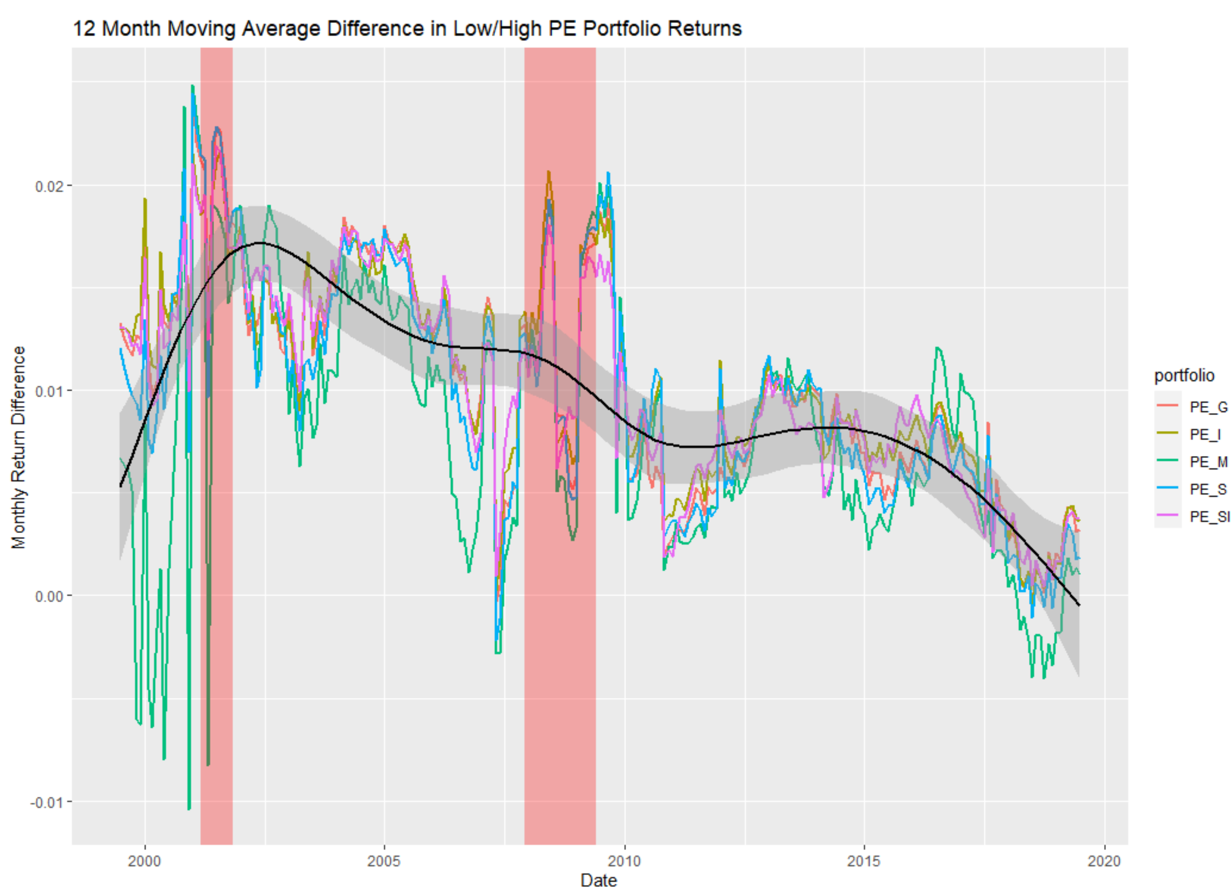
Table 6: FPE Portfolio Stats

Portfolio	Mean	SD	Sharpe
FPEHighM	0.00390	0.04475	0.08725
FPELowM	0.02484	0.04473	0.55548
FPEHighS	0.00332	0.04377	0.07588
FPELowS	0.02546	0.04516	0.56383
FPEHighI	0.00328	0.04384	0.07481
FPELowI	0.02559	0.04504	0.56819
FPEHighG	0.00335	0.04388	0.07644
FPELowG	0.02546	0.04496	0.56623
FPEHighSI	0.00349	0.04421	0.07895
FPELowSI	0.02569	0.04432	0.57962

[9] The mean column in Tables 5 and 6 represents the arithmetic mean of 1-month future returns of the portfolios between 1999-7-31 and 2019-7-31.

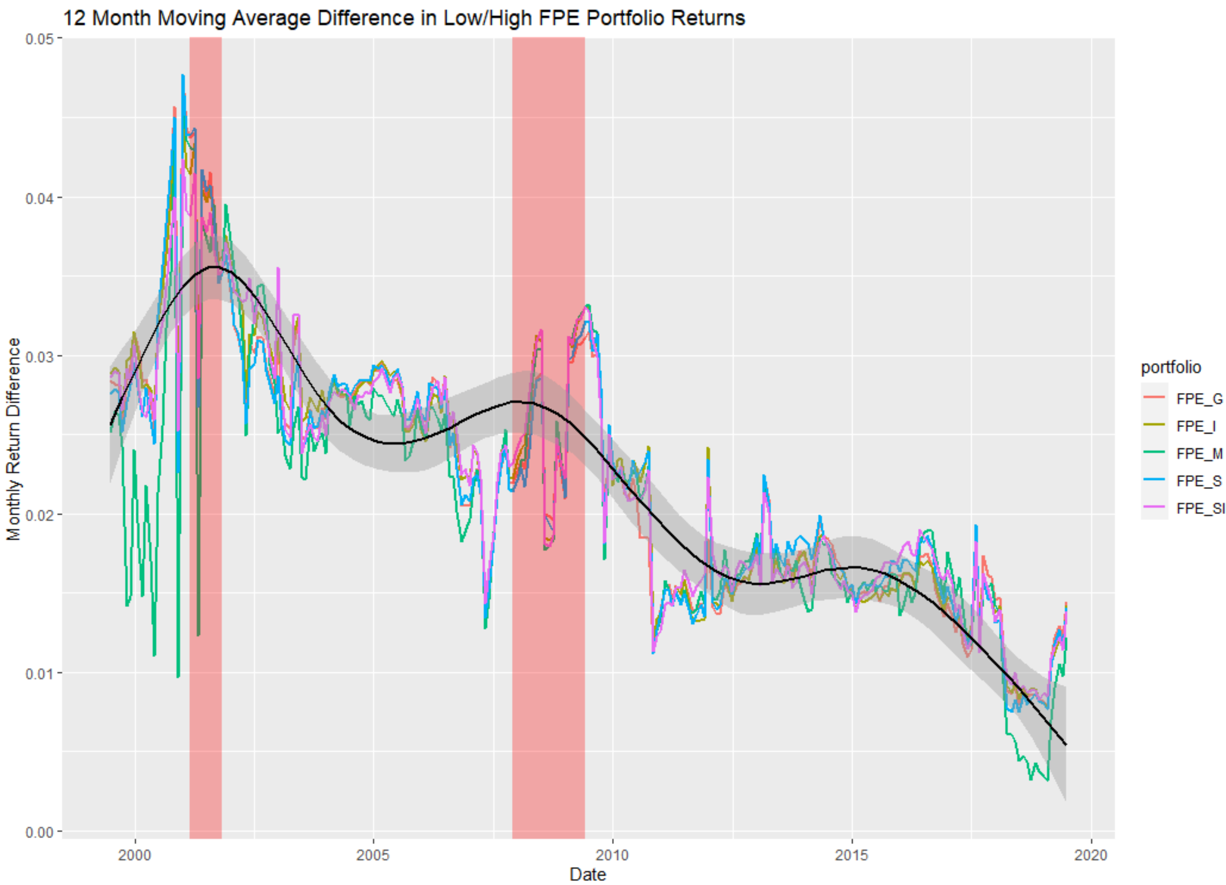
However, the outperformance of low P/E portfolios is not consistent over time. Figures 6 and 7 show the 12-month moving average of low/high difference of portfolio returns. All portfolio differences show a similar pattern. Low P/E portfolios outperformed their high counterparts by a significant margin during the 1999-2009 period, then the difference declined to the point where it is near or below 0 by 2018. Highlighted in red are dates when the US was in a recession. Within these dates are local maximums for the difference in returns, which temporarily buck the overall downward trend before reverting to it.

Figure 6: 12 Month Moving Average Difference of Low/High PE Portfolio Returns Grouped by Portfolio Classification



[10] Recession periods are defined by the national bureau of economic research.

Figure 7: 12 Month Moving Average Difference of Low/High FPE Portfolio Returns Grouped by Portfolio Classification with Recession Periods Highlighted in Red.



Breaking the data down into two periods, before and after 2010, the difference in returns becomes apparent. Tables 7 and 8 show the arithmetic mean returns, standard deviations and Sharpe ratios for the two periods. If the low PE effect was consistent after adjusting for risk, then the difference in Sharpe should remain consistent, but the difference in Sharpe ratios for the later period is also significantly lower than the Sharpe ratio difference for the former. This suggest that the decline in outperformance cannot be strictly explained by return variability.

[11] In Figures 6 and 7, the black trendline is the result of exponentially smoothing all returns.

Table 7: Portfolio Statistics from 1999-2009

Portfolio	Mean	SD	Sharpe
PEHighM	0.0092749	0.0478918	0.1936635
PELowM	0.0201200	0.0469486	0.4285532
PEHighS	0.0079762	0.0456320	0.1747939
PELowS	0.0214684	0.0482460	0.4449787
PEHighI	0.0076367	0.0457094	0.1670699
PELowI	0.0219649	0.0480355	0.4572640
PEHighG	0.0076076	0.0456681	0.1665855
PELowG	0.0218214	0.0480170	0.4544515
PEHighSI	0.0078834	0.0458021	0.1721198
PELowSI	0.0218582	0.0476153	0.4590579
FPEHighM	0.0009767	0.0489134	0.0199681
FPELowM	0.0284073	0.0456531	0.6222420
FPEHighS	0.0002946	0.0468047	0.0062949
FPELowS	0.0291208	0.0469732	0.6199441
FPEHighI	0.0000524	0.0468962	0.0011165
FPELowI	0.0294774	0.0467833	0.6300841
FPEHighG	0.0002250	0.0469730	0.0047897
FPELowG	0.0292368	0.0466822	0.6262938
FPEHighSI	0.0005334	0.0470161	0.0113454
FPELowSI	0.0294460	0.0461957	0.6374190

Table 8: Portfolio Statistics from 2010-2019

Portfolio	Mean	SD	Sharpe
PEHighM	0.0116524	0.0400100	0.2912377
PELowM	0.0163940	0.0432142	0.3793669
PEHighS	0.0112538	0.0398904	0.2821173
PELowS	0.0168300	0.0430483	0.3909569
PEHighI	0.0109270	0.0403836	0.2705793
PELowI	0.0172490	0.0425495	0.4053861
PEHighG	0.0111146	0.0403792	0.2752561
PELowG	0.0169438	0.0425371	0.3983306
PEHighSI	0.0111811	0.0409199	0.2732442
PELowSI	0.0170500	0.0418260	0.4076403
FPEHighM	0.0071664	0.0395646	0.1811314
FPELowM	0.0208763	0.0435278	0.4796083
FPEHighS	0.0066934	0.0400621	0.1670754
FPELowS	0.0213845	0.0428829	0.4986709
FPEHighI	0.0068751	0.0400599	0.1716211
FPELowI	0.0212632	0.0428057	0.4967390
FPEHighG	0.0068396	0.0400640	0.1707179
FPELowG	0.0212449	0.0427659	0.4967721
FPEHighSI	0.0067838	0.0408034	0.1662554
FPELowSI	0.0214984	0.0419284	0.5127418

Carhart Model

Tables 9 and 10 show the coefficient p-values and adjusted r-squares from running linear regressions for the portfolio returns on the four factors that make up the Carhart model. For the time period 1999-2009, the Carhart models have adjusted r-squares of 84%-93% and p-values of near zero for all the MKTRF, SMB, and HML coefficients. While the MOM coefficients also have p-values close to zero for low ratio portfolios, the p-values for the high ratio portfolios are not low enough to allow MOM to give any explanatory insight as to why low P/E ratio portfolios outperformed in this period.

Table 9: Carhart Model Coefficeint P-values For 1999-2009 Portfolios

Portfolio	intercept	mktrf	smb	hml	umd	adj_r_sqr
PEUnderSI	0.0000000	0	0	0	0.0011077	0.8840971
PEOverSI	0.1424062	0	0	0	0.8116711	0.9092873
PEUnderI	0.0000000	0	0	0	0.0007010	0.8867790
PEOverI	0.1880376	0	0	0	0.7201554	0.9049594
PEUnderG	0.0000000	0	0	0	0.0004327	0.8916013
PEOverG	0.1698462	0	0	0	0.8895275	0.9018703
PEUnderS	0.0000000	0	0	0	0.0002083	0.8910309
PEOverS	0.1085850	0	0	0	0.8718203	0.9004755
PEUnderM	0.0000000	0	0	0	0.0001958	0.8659884
PEOverM	0.0149878	0	0	0	0.5869569	0.9158918
FPEUnderSI	0.0000000	0	0	0	0.0085925	0.8648885
FPEOverSI	0.0006902	0	0	0	0.3605660	0.9151860
FPEUnderI	0.0000000	0	0	0	0.0073786	0.8652845
FPEOverI	0.0001183	0	0	0	0.4323424	0.9197601
FPEUnderG	0.0000000	0	0	0	0.0097755	0.8662078
FPEOverG	0.0003463	0	0	0	0.2426940	0.9197454
FPEUnderS	0.0000000	0	0	0	0.0088410	0.8662890
FPEOverS	0.0006229	0	0	0	0.3150958	0.9171270
FPEUnderM	0.0000000	0	0	0	0.0078976	0.8442760
FPEOverM	0.0017176	0	0	0	0.4403366	0.9298176

Like for the first time period, applying the Carhart model to the 2010-2019 data also results in high adjusted r-squares and very low p-values for MKTRF and SMB. Unlike the first period, the p-values of HML become less reliable as the classification becomes broader. The portfolio PEHighSI, which uses sub-industry median PE to define low/high, has a p-value of .009. While the portfolio PEHighM, which uses the market median PE, has a p-value of .51. Additionally, p-values for MOM in the PE models are also significantly different compared to the prior period. The p-values for these range from .005 to .071 and reach their lowest values as the classification becomes broader.

Table 10: Carhart Model Coefficeint P-values For 2010-2019 Portfolios

Portfolio	intercept	mktrf	smb	hml	umd	adj_r_sqr
PEUnderSI	0.0000000	0	0	0.0079275	0.0661693	0.9679688
PEOverSI	0.6074359	0	0	0.0096938	0.0448125	0.9785959
PEUnderI	0.0000000	0	0	0.0022857	0.0578098	0.9685441
PEOverI	0.6100331	0	0	0.0431545	0.0536290	0.9782059
PEUnderG	0.0000000	0	0	0.0028066	0.0700790	0.9668397
PEOverG	0.5039601	0	0	0.0387149	0.0285381	0.9793862
PEUnderS	0.0000000	0	0	0.0018888	0.0338780	0.9691369
PEOverS	0.3683821	0	0	0.0603381	0.0156511	0.9776833
PEUnderM	0.0000000	0	0	0.0000019	0.0162277	0.9685738
PEOverM	0.2860667	0	0	0.5125206	0.0067809	0.9754594
FPEUnderSI	0.0000000	0	0	0.0008764	0.9780866	0.9640369
FPEOverSI	0.0000108	0	0	0.1040642	0.8844712	0.9797072
FPEUnderI	0.0000000	0	0	0.0015707	0.6456004	0.9660003
FPEOverI	0.0000403	0	0	0.0736600	0.7987362	0.9795111
FPEUnderG	0.0000000	0	0	0.0006473	0.9233722	0.9648927
FPEOverG	0.0000298	0	0	0.1999198	0.7375462	0.9796781
FPEUnderS	0.0000000	0	0	0.0006143	0.8351689	0.9652352
FPEOverS	0.0000281	0	0	0.2459481	0.9157065	0.9781817
FPEUnderM	0.0000000	0	0	0.0000046	0.9649144	0.9631266
FPEOverM	0.0004828	0	0	0.3734864	0.7422153	0.9753111

Tables 11 shows the coefficient values from applying the Carhart model on the 1999-2009 time period. For this period, the MKTRF coefficients for all low P/E portfolios are lower than their high P/E portfolio counterparts. This indicates that during this time period, low P/E portfolios faced less systemic risk. The SMB coefficients significance in explaining the difference in portfolio returns is less clear. Among the low P/E portfolios, the SMB coefficients are slightly lower than their high PE portfolio counterparts except for the market portfolios.

The HML coefficients for the low P/E portfolios are significantly larger than their high P/E portfolio counterparts. The difference between low/high HML coefficients becomes larger as the classification becomes broader. Given the tendency of high book value securities to outperform low book value securities, the higher HML coefficients for low P/E ratio portfolios can explain large portion of why low P/E ratios portfolios outperformed during this time period.

Table 11: Carhart Model Coefficients For 1999-2009 Portfolios

Portfolio	intercept	mktrf	smb	hml	umd
PELowSI	0.0157146	0.7398793	0.3668765	0.4895431	-0.0968566
PEHighSI	0.0021980	0.8296825	0.3059267	0.4290115	-0.0059677
PELowI	0.0156076	0.7466619	0.3730749	0.5002002	-0.1009556
PEHighI	0.0020091	0.8232541	0.3048000	0.4210149	-0.0091523
PELowG	0.0154385	0.7459528	0.3737570	0.5134774	-0.1029793
PEHighG	0.0021192	0.8220875	0.3032889	0.4068220	-0.0035867
PELowS	0.0150884	0.7450486	0.3706739	0.5124739	-0.1096231
PEHighS	0.0025020	0.8269230	0.3034993	0.4028853	0.0041997
PELowM	0.0138529	0.7080607	0.2964471	0.5512910	-0.1193465
PEHighM	0.0036987	0.8629432	0.3754582	0.3632188	0.0136631
FPELowSI	0.0233040	0.7219112	0.3571281	0.4820574	-0.0813803
FPEHighSI	-0.0051673	0.8392254	0.3212390	0.4318275	-0.0226862
FPELowI	0.0233980	0.7343262	0.3450067	0.4931256	-0.0839401
FPEHighI	-0.0057453	0.8388695	0.3306848	0.4265862	-0.0188945
FPELowG	0.0229707	0.7289987	0.3479423	0.5127518	-0.0802950
FPEHighG	-0.0053228	0.8412735	0.3229576	0.4020974	-0.0282560
FPELowS	0.0227344	0.7242227	0.3597453	0.5208238	-0.0815463
FPEHighS	-0.0051600	0.8476264	0.3119660	0.3926194	-0.0246862
FPELowM	0.0220238	0.6920959	0.3052051	0.5603053	-0.0876589
FPEHighM	-0.0044943	0.8784363	0.3675383	0.3543320	-0.0181024

Table 12 shows the coefficient values from applying the Carhart model on the 2010-2019 time period. Unlike the earlier period, the MKTRF coefficients for the low P/E portfolios are nearly the same or higher than their high P/E portfolio counterparts. This implies low P/E ratio securities faced more systemic risk than their high ratio counterparts. The relationship between low and high P/E portfolio SMB coefficients also switched direction during this period. The SMB coefficients of the low P/E portfolios are slightly less than their counterparts except for those based on market classification.

Among the PE portfolio models with p-values less than .05, the low MOM beta coefficients of the low ratio portfolios are less than their counterparts. But given the low coefficient values and the more questionable p-values when compared to SMB or MKTRF coefficients, the momentum factor explains just a small proportion of difference in low/high PE portfolio returns.

The HML coefficients showed the most drastic changes. While the relationship between low and high portfolio HML coefficients did not change direction, all coefficient values decreased greatly. The HML coefficient for the portfolio PEHighM, for example, decreased from .36 to less than -.02. This decease corresponds with the increase in p-values for the coefficient seen in tables 9 and 10.

Table 12: Carhart Model Coefficients For 2010-2019 Portfolios

Portfolio	intercept	mktrf	smb	hml	umd
PELowSI	0.0070353	0.9486892	0.4391247	0.1210191	-0.0618327
PEHighSI	0.0003885	0.9310894	0.5194378	0.0936438	0.0538194
PELowI	0.0069704	0.9667842	0.4439136	0.1416519	-0.0646004
PEHighI	0.0003827	0.9187916	0.5052004	0.0720027	0.0513088
PELowG	0.0067866	0.9618366	0.4499792	0.1419986	-0.0631321
PEHighG	0.0004886	0.9227037	0.5043101	0.0717328	0.0569111
PELowS	0.0065545	0.9744820	0.4504410	0.1446433	-0.0725517
PEHighS	0.0006765	0.9127514	0.4973013	0.0667918	0.0647611
PELowM	0.0063770	0.9585387	0.4772750	0.2361650	-0.0840782
PEHighM	0.0008407	0.9276409	0.4709861	-0.0241202	0.0763082
FPELowSI	0.0109121	0.9596185	0.4385882	0.1628226	0.0009678
FPEHighSI	-0.0034529	0.9242386	0.5037292	0.0564268	-0.0037381
FPELowI	0.0104847	0.9787209	0.4463388	0.1530898	-0.0161071
FPEHighI	-0.0031534	0.9090279	0.4981011	0.0614202	0.0064772
FPELowG	0.0104490	0.9779953	0.4523441	0.1685338	0.0034156
FPEHighG	-0.0032027	0.9094051	0.4932327	0.0436398	-0.0084860
FPELowS	0.0105765	0.9747547	0.4542940	0.1685162	-0.0073558
FPEHighS	-0.0033382	0.9114396	0.4973275	0.0409837	-0.0027827
FPELowM	0.0100689	0.9760132	0.4887800	0.2444299	0.0016319
FPEHighM	-0.0028580	0.9098653	0.4599259	-0.0328452	-0.0090549

In comparing the results from the two periods, there is much evidence to suggest the P/E effect has decreased in the past twenty years largely due to the HML factor becoming less significant, and to a smaller degree the SMB effect becoming stronger with high P/E portfolios than with low P/E portfolios.

Part V: Conclusion

Investing in low PE or FPE securities has long been a held up as a strategy to outperform the market. Historically there is much evidence of portfolios consisting of low P/E securities outperforming high P/E portfolios, even after adjusting for risk. This effect has often been described as a market anomaly, for it should not exist if markets are efficient.

However this tendency of low P/E ratio portfolios to outperform has decreased in the past 20 years to the point where low P/E portfolios on average have the same or lower returns than high P/E portfolios, regardless of classification, or use of trailing or forward earnings.

During the 1999-2009 period, the P/E effect was decreasing, but still significant. Its existence can largely be explained by low P/E portfolios having a stronger relationship to high book value portfolios when compared to high P/E portfolios. To a lesser degree it can also be explained by low P/E portfolios having a stronger relationship to small cap portfolios.

The P/E effect largely broke down during the 2010-2019 period as low P/E portfolios no longer significantly outperformed. To a smaller degree this can be explained low P/E portfolios becoming more associated with large cap portfolios which historically underperform. But the deterioration can mainly be explained by its weaker relationship to portfolios based on high book values as represented by the HML factor in the Carhart model. The HML factor itself, became less relevant during this period. This questions the original notion that high book value securities outperform low book value securities and whether or not HML is a good proxy for risks not covered by the MKTRF coefficient such as default or liquidity risk.

The breakdown of the P/E effect and less relevance of the HML factor, could be the result of markets simply becoming more efficient. In an efficient market higher returns are associated with higher risks. The three most significant of these risks being market, liquidity, and default. While HML has been thought of as a proxy for default risk, more recent papers in the matter have concluded it may not be (Gharghori-Chan 2007). MRKTF and SMB are seen as much stronger proxies for market risk and liquidity risk respectively than the HML factor. If so, then the decreasing HML and P/E effects may be the result of markets becoming more efficient.

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