AUGMENTED VALUE WITH MOMENTUM

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Abstract

This study explores the implementation of value strategies using augmentation with a wide range of momentum anomalies. The strategy uses an equal weight between value and momentum, implemented with data from 1972 to 2020. Among the 15 anomalies considered, there were two significant value anomalies and seven significant momentum anomalies. Various definitions state that momentum reduces the risk of an equity value portfolio across the board in risk-adjusted return measures. The increases in performance with lower volatility are because value strategy helps momentum during momentum crashes, coupled with negative correlations between these two anomalies. Momentum anomalies also increase the overall average monthly returns of value strategies. The study also compares how the augmented q-factor and Fama-French factor models explain value when augmented with momentum portfolios. The augmented q-factor model outperforms the Fama-French five and six-factor models using the number of significant α's as criteria. Using the adjusted R^2, the Fama-French six-factor model outperforms in explaining the augmented portfolios.

Keywords: value; momentum; investing; empirical asset pricing

1. INTRODUCTION

Value and momentum are two well-known strategies that outperform in different countries and various assets, according to Asness, Moskowitz, and Pedersen (2013). In addition, augmentation of the two strategies gives even higher returns and lower risk than using only one of these components. The construction of Asness, Moskowitz, and Pedersen (2013) uses particular definitions of value and momentum throughout all asset classes and different markets. This study takes a different angle,

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extending the concept by focusing on the US equity market. Portfolios are constructed from different definitions for value anomalies and momentum anomalies. This uses various definitions of momentum that can be implemented with the value strategy. This differs from the work of O'Shaughnessy (2011), which shows the screening of value and momentum stocks, called “trending value.” O'Shaughnessy (2011) first found value stocks using various definitions, then ranked these stocks based on the momentum of each value stock to construct the trending-value portfolio. This study uses a different implementation. The portfolio of value and momentum will be constructed separately and then mixed using 50:50 weights, similarly to the construction used in Asness, Moskowitz, and Pedersen (2013). In addition, this study also offers some explanation for why a momentum strategy can be implemented well for the value portfolio at a particular time. Finally, it uses the most up-to-date empirical asset pricing models, such as the augmented q-factor (AQ) model from Hou et al. (2021), the Fama-French five-factor (FF5) model from Fama and French (2015), and the Fama-French six-factor (FF6) model from Fama and French (2018), to explain and measure the performance of the constructed value portfolios.

The value investment or value portfolio has been known since the work of Graham and Dodd (2004) and Graham et al. (2006). Portfolios that invest in value stocks with low price to book (P/B) or price to earnings (P/E), outperform growth stocks with high P/B or high P/E. To show how value stocks outperform growth stocks, Basu (1977) constructed portfolios based on the decile of P/E. This shows that the lowest decile of the P/E portfolio outperforms the highest decile. Rosenberg, Reid, and Lanstein (1985) also defined value portfolios using a book to market ratio (B/M), which is the flip side of the P/B ratio, finding that the high B/M portfolio (value portfolio) outperformed the low B/M portfolio (growth portfolio). Many studies have found many other ratios which can be used to define value portfolios. However, Hou, Xue, and Zhang (2015) argue that some of these definitions might be redundant. Therefore, this study employs various value definitions corresponding to Hou, Xue, and Zhang (2015).

Another well-known stock investment strategy is momentum. Momentum portfolios also outperform the market in the long term. For the short term, buying stocks with high momentum can outperform low momentum stocks. The strategy relies on past returns of each stock. For example, the notable momentum portfolio is the price momentum from the previous 12 months excluding the recent month. It holds stocks with previous high momentum and short low momentum for one month. Hou, Xue, and Zhang (2015) call this R11-1. The strategy is similar to those described by Jegadeesh and Titman (1993), Fama and French (1996), and Asness, Moskowitz, and Pedersen (2013).

This study also shows that the R11-1 is a significant anomaly and performs well from 1972 to 2020. The study also considers other momentum strategies, such as earning surprise, abnormal returns around earning announcement, and industry momentum.

The results from the study are as follows. Two value anomalies are significant. In addition, seven momentum anomalies are significant. The augmented value with momentum portfolio consists of these value and momentum anomalies. The augmented value that invests dynamically 50:50 with momentum, results in a higher risk-adjusted return (Sharpe ratio). Momentum helps the value portfolio to increase the overall monthly average. On the other hand, value anomalies help momentum during momentum crashes, as described in Daniel and Moskowitz (2016). The empirical asset pricing model explains the augmented value with momentum portfolio in different ways. The AQ model outperforms in terms of the number of significant α's in explaining the augmented value with momentum portfolios. However, the FF6 model gives the highest overall adjusted R^2 to explain the augmented value with momentum portfolios.

This study proceeds with the following sections. Section 2 explains the methodology with the portfolio constructions and different measurements. Section 3 discusses the data. Section 4 shows the results of the study. The final section concludes and discusses the study.

2. METHODOLOGY

2.1 Anomalies and Portfolio Constructions

The long-short (zero cost) portfolios for each anomaly of value and momentum are given by the highest decile minus the lowest decile, in a similar way to Asness, Moskowitz, and Pedersen (2013). These follow Hou, Xue, and Zhang (2015) for the definitions and representative variables for value and momentum. The study obtains its data from the global-q.org website under the "Testing Portfolios" section. All definitions and the methodology to construct each anomaly can be found in Hou, Xue, and Zhang (2015). The analysis in Hou, Xue, and Zhang (2015) begins in 1972. The value portfolios consist of 1) B/M: book-to-market from Rosenberg, Reid, and Lanstein (1985); 2) Rev: reversal in price from De Bondt and Thaler (1985); 3) D/P: dividend yield from Litzenberger and Ramaswamy (1979); 4) A/ME: market leverage from Bhandari (1998); 5) E/P: Earnings-to-price from Basu (1977); 6) S/P: Sales growth from Lakonishok, Shleifer, and Vishny (1994); and 7) Dur: equity duration from Dechow, Sloan and Soliman (2004). The study leaves out the LTG Long-term growth forecasts of the analysis from La Porta (1996); NO/P: net payout yield from Boudoukh et al. (2007); and O/P: payout yield from Boudoukh et al. (2007), as these are not included in the database at the start of 1972. The study uses S/P (sales-to-price) rather than 'sales growth' from Lakonishok, Shleifer, and Vishny (1994) due to the availability of the database.

Variables for momentum consist of 1) SUE-1: earning surprise with a one month holding period from Foster, Olsen, and Shevlin (1984); 2) Abr-1: cumulative abnormal stock returns around earnings announcements; 3) Abr-6: cumulative abnormal stock returns around an earnings announcement with a six month holding period; 4) R11-1: price momentum with 11 month prior returns and a one month holding period from Fama and French (1996); 5) SUE-6: Earning surprise with a six month holding period from Foster, Olsen, and Shevlin (1984); 6) R6-1: price momentum with six month prior returns and a one month holding period; 7) R6-6: price momentum with six month prior returns and six months holding period from Jegadeesh and Titman (1993); and 8) I-Mom: industry momentum from Moskowitz and Grinblatt (1999). The study leaves out revisions in analysts' earnings forecasts with one-month and six-month holding periods (RE-1 and RE-6), as this data begins in the middle of 1976 not the start of 1972. The I-Mom from the database is separated into six portfolios rather than deciles. The sixth-highest and the lowest portfolio of I-Mom are therefore subtracted.

In total, there are seven value anomalies and eight momentum anomalies. The study reports the summary statistics of value and momentum anomalies in the average monthly returns, and t-statistics with the associated p-values. After retrieving the significant anomalies, each variable was then used, mixing with momentum at a weight of 50:50, similar to the method described by Asness, Moskowitz, and Pedersen (2013). The construction of the average returns each month implies that each augmented portfolio dynamically adjusts a 50% weight between each strategy each month after realizing the monthly return.

2.2 Empirical Asset Pricing Models

The study employs the most sought-after empirical asset pricing models to explain each augmented portfolio. More specifically, the AQ model from Hou et al. (2021) is given in the form of:

$$r_i(t) - r_f(t) = \alpha_i + \beta_{i,MKT}(r_{MKT}(t) \\ -r_f(t)) + \beta_{i,ME}r_{ME}(t) + \beta_{i,\frac{I}{A}}r_{\frac{I}{A}}(t) \\ +\beta_{i,ROE}r_{ROE}(t) + \beta_{i,EG}r_{EG}(t) + \epsilon_i(t)$$

The return definitions are the following: $r_i - r_f$ is the excess asset or portfolio return, which in this case is the mix of the long-short portfolio; r_f is the risk free rate; $r_{MKT}(t) - r_f(t)$ is the excess market return; r_{ME} is the size factor; $r_{I/A}$ is the investment factor; r_{ROE} is the profitability factor; and r_{EG} is the expected growth factor. In addition, the study employs the FF6 model from Fama and French (2018) to analyze the augmented portfolio in the relationship of:

$$r_i(t) - r_f(t) =$$
$$\alpha_i + \beta_{i,MKT}\left(r_{MKT}(t) - r_f(t)\right)$$
$$+\beta_{i,SMB} r_{SMB}(t) + \beta_{i,HML} r_{HML}(t)$$
$$+\beta_{i,RMW} r_{RMW}(t) + \beta_{i,CMA} r_{CMA}(t)$$
$$+\beta_{i,UMD} r_{UMD}(t) + \epsilon_i(t)$$

The return definitions are as follows: $r_i - r_f$ is the excess return of the asset or portfolio return, which in this case is the mix of the long-short portfolio; r_f is the risk free rate; $r_{MKT}(t) - r_f(t)$ is the excess market return; r_{SMB} is the size factor; r_{HML} is the value factor; r_{RMW} is the profitability factor; r_{CMA} is the investment factor; and r_{UMD} is the momentum factor. The FF5 model is the same as the FF6 model excluding the momentum factor (UMD). All the dependent variables are mixtures of the long-short value and the long-short momentum. Therefore, when using these augmented portfolios, it is not necessary to subtract the risk-free rate again before regression. The study reports the α of each empirical asset pricing model, the t-statistics of each α, and the adjusted R^2 of each model, to see how each model explains the augmented portfolios.

3. THE DATA

All deciles of value, momentum, and the augmented q-factor model factors were taken from the global-q.org website[1] under the "Testing Portfolios" section, following Hou, Xue, and Zhang (2015). The value anomalies in the global-q.org website are called value-versus-growth. This study uses only the highest decile and the lowest decile for each anomaly, and uses the same names for the momentum and value anomalies as shown in the website. For example, momentum anomalies consist of Abr1, Abr6, …, Sue6. The value anomalies consist of Bm, Bmj, …, Vhp. The definition for each anomaly is indicated in the "Technical Document: Testing Portfolios[2]." The factors in the Fama-French factor models and risk-free rate are taken from Kenneth French's data library[3]. Analysis was carried out on data from 1972, similarly to Hou, Xue, and Zhang (2015) and Hou et al. (2021), until 2020. Therefore, the study screens only anomalies that were available in these periods. After retrieving all the data, this study used only the significant anomalies to be considered in the augmented value and momentum, similar to use in the previous literature. The study uses the R program to arrange the data and implement econometric models.

4. RESULTS

The results of the value and momentum anomalies are shown in Table 1 and Table 2 respectively.

[1] http://global-q.org/testingportfolios.html
[2] http://global-q.org/uploads/1/2/2/6/122679606/portfoliostd_2021april.pdf
[3] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

After retrieving all the significant anomalies from both value and momentum strategies, each anomaly was then mixed from each type to construct the augmented portfolios. The study illustrates the performance and risk of the augmented value with momentum with B/M and S/P in Table 3 and Table 4, respectively. Table 5 and Table 6 analyze how AQ, FF5, and FF6 explain the augmented portfolios using the value indicators B/M and S/P, respectively.

4.1 Finding Significant Anomalies

Table 1 reports the sample mean (m), t-statistic (t_m), and p-value (p) of each anomaly's returns. The only two value anomalies that are significant are B/M, which has an average monthly return of 0.0035, and t-statistic of 1.6643, and S/P which has an average monthly return of 0.0039 and a t-statistic of 2.0354. The earning yield (E/P) and equity duration (Dur) are not significant, which is different from Hou, Xue, and Zhang (2015). This is also in line with Linnainmaa and Roberts (2018). Even though, value anomalies can outperform the market in the long run, some value anomalies can underperform during particular times. The S/P is the most significant value anomaly in the period from 1972 to 2020, according to the t-statistics. Therefore, the B/M and S/P are the only two candidates for the next procedure of augmenting with the significant momentum strategies.

Table 2 shows that all the momentum anomalies are significant except the SUE-6 momentum. Contrastingly, the SUE-6 is significant in Hou, Xue, and Zhang (2015). The highest average monthly return of the momentum anomaly is R11-1 at 0.0109. R11-1 is also a momentum factor (UMD) in Fama and French (2018) for Fama-French's 6-factor model. The lowest monthly averages are for Abr-6 and I-Mom at 0.0036 per month. The most significant momentum anomaly is Abr-1, with a t-statistic of 5.4333.

Table 1 Value Anomalies from 1972 to 2020

	B/M	Rev	D/P	A/ME	E/P	S/P	Dur
	*					**	
m	0.0035	-0.0015	0.0018	0.0022	0.0028	0.0039	-0.0024
t_m	1.6643	-0.81475	0.76039	1.1104	1.4176	2.0354	-1.2387
p	0.09659	0.4155	0.4473	0.2673	0.1569	0.04226	0.2160

Note: This table illustrates the sample mean (m), the t-statistic (t_m), and the p-value (p) of each anomaly's returns. *, **, and *** represent the significant level at 0.1, 0.05, and 0.01, respectively.

Table 2 Momentum Anomalies from 1972 to 2020

	SUE-1	Abr-1	Abr-6	R11-1	SUE-6	R6-1	R6-6	I-Mom
	***	***	***	***		**	***	**
m	0.0043	0.0074	0.0036	0.0109	0.0017	0.0059	0.0079	0.0036
t_m	2.9972	5.4333	3.9668	3.5551	1.3598	2.0197	3.3894	2.4671
p	0.0028	0.0000	0.0000	0.0004	0.1744	0.0439	0.0007	0.0139

Note: This table illustrates the sample mean (m), the t-statistic (t_m), and the p-value (p) for each of the anomaly's returns. *, **, and *** represent the significance level at 0.1, 0.05, and 0.01, respectively.

Therefore, all momentum anomalies were included, except for SUE-6 for the construction of the augmented value portfolios with momentum, which is similar to the analysis of Hou, Xue, and Zhang (2015).

4.2 Augmented Value with Momentum

Table 3 shows the performance and risk of the augmented B/M with momentum anomalies. The shaded area represents the augmented portfolios. The m(50:50) is the monthly average return for each augmented portfolio. The risk measure is the standard deviation σ(50:50). The Sharpe ratios are shown in row m/σ (50:50) of the table. The table also reports correlations between B/M and other momentum anomalies, ρ(B/M,:), as well as the cumulative return in the last row, Cumulative (50:50). It also includes the performance and risk of the pure anomaly in the non-shaded area. The momentum strategies improve the B/M anomaly, in all cases, in terms of the average monthly return and the Sharpe ratios. For example, the pure B/M anomaly receives a 0.0035 monthly return, while the augmented B/M with R11-1 results in an average return of 0.0072. All momentum anomalies receive a lower average return after augmenting with B/M. For example, the pure R6-6 receives an average monthly return of 0.0079, while the augmented B/M with R6-6 obtains 0.0057. However, the augmented value B/M with momentum anomalies, except Abr-1 and Abr-6, outperform the pure momentum anomalies using the Sharpe ratio. For example, the pure R6-6 receives a Sharpe ratio of 0.1398, while the augmented B/M with R6-6 obtains 0.2145. This is because the standard deviation of the augmented value with momentum decreases from the pure momentum. For example, the pure R6-6 has a standard deviation of 0.0562, but when augmented with B/M has a standard deviation of 0.0265. The Sharpe ratios for the augmented B/M with momentum all increase from the pure B/M strategy. The downside of the augmented value is with the standalone Abr-1 and Abr-6. Here the augmented versions have lower

Table 3 The Augmented B/M with Momentum from 1972 to 2020

	B/M	SUE-1	Abr-1	Abr-6	R11-1	R6-1	R6-6	I-Mom
m	0.0035	0.0043	0.0074	0.0036	0.0109	0.0059	0.0079	0.0036
σ	0.05102	0.0346	0.0328	0.0220	0.0742	0.0709	0.0562	0.0353
m/σ	0.06863	0.1236	0.2241	0.1636	0.1466	0.0833	0.1398	0.1017
ρ(B/M,:)		-0.5277	-0.2586	-0.3332	-0.5163	-0.4046	-0.5161	-0.3984
m (50:50)		0.0039	0.0054	0.0035	0.0072	0.0047	0.0057	0.0035
σ (50:50)		0.0220	0.0265	0.0242	0.0324	0.0343	0.0265	0.0246
m/σ (50:50)		0.1768	0.2046	0.1468	0.2219	0.1372	0.2145	0.1444
Cumulative (50:50)		8.5329	19.6611	6.7805	49.8052	11.1973	22.7680	6.7277

Note: This table illustrates the sample mean (m), the standard deviation of each mean (σ), and the Sharpe ratio of each anomaly (m/σ) or each anomaly's returns. It provides the correlation between B/M with each momentum anomaly ρ(B/M,:). In addition, it provides the same statistics for the augmented value with the addition of the cumulative returns (Cumulative) from 1972 to 2020, in the shaded area.

average returns because B/M has a lower average return than Abr-1, and Abr-6. The augmented value with Abr-1 and Abr-6 have lower volatility. The performance in the Sharpe ratio is lower when compared to the standalone Abr-1 and Abr-6. The highest Sharpe ratio is the augmented B/M with R11-1. This achieves a Sharpe ratio of 0.2219 with a cumulative return of 49.8052 over 39 years. Overall, the augmented value portfolios improve the Sharpe ratio partly due to the relationship between value and momentum with negative correlations.

Table 4 reports similar augmented value measures to those shown in Table 3 using S/P instead of B/M as the value anomaly. The S/P anomaly has negative correlations with all momentum anomalies, similarly to B/M. The average monthly return of S/P is 0.0039. The S/P augmented with other momentum anomalies improves from the pure S/P, except Abr-6 (at 0.0037) and I-Mom (at 0.0037). The Sharpe ratio from the S/P is 0.0839. All momentum anomalies improve the Sharpe ratio for the S/P anomaly. The highest Sharpe ratio is for the S/P augmented with Abr-1 (0.2184). The second highest is for R11-1, which is also the best Sharpe ratio for the B/M case. Though, augmenting S/P with R11-1 results in the best cumulative return from 1972 to 2020. S/P also helps most momentum anomalies by increasing the Sharpe ratios. For example, the Sharpe ratio of SUE-1 increases from 0.1236 to 0.1727 for

Table 4 The Augmented S/P with Momentum from 1972 to 2020

	S/P	SUE-1	Abr-1	Abr-6	R11-1	R6-1	R6-6	I-Mom
m	0.0039	0.0043	0.0074	0.0036	0.0109	0.0059	0.0079	0.0036
σ	0.0460	0.0346	0.0328	0.0220	0.0742	0.0709	0.0562	0.0353
m/σ	0.0839	0.1236	0.2241	0.1636	0.1466	0.0833	0.1398	0.1017
ρ(S/P,:)		-0.3422	-0.1836	-0.2056	-0.2463	-0.2109	-0.2799	-0.1445
m (50:50)		0.0041	0.0056	0.0037	0.0074	0.0049	0.0059	0.0037
σ (50:50)		0.0236	0.0257	0.0233	0.0385	0.0380	0.0309	0.0269
m/σ (50:50)		0.1727	0.2184	0.1597	0.1912	0.1286	0.1894	0.1386
Cumulative(50:50)		9.2670	22.0815	7.6048	48.2844	11.3961	23.3924	7.2044

Note: This table illustrates the sample mean (m), the standard deviation of each mean (σ), and the Sharpe ratio of each anomaly (m/σ), or each anomaly's returns. It provides a correlation between S/P with each momentum anomaly ρ(S/P,:). In addition, it provides the same statistics for the augmented value with the addition of cumulative returns (Cumulative) from 1972 to 2020, in the shaded area.

the augmented S/P with SUE-1. On the other hand, the Sharpe ratios of the augmented S/P with Abr decrease (0.2241 to 0.2184 for Abr-1, and 0.1636 to 0.1597 for Abr-6). When considering the standalone momentum strategy, the augmented value with momentum might reduce the performance of SUE-1, Abr-1, and Abr-6. For example, the augmented value for SUE-1 results in a lower average return. However, it increases the Sharpe ratio. The augmented value for Abr-1 reduces volatility, and also reduces the Sharpe ratio. The augmented value for Abr-6 increases volatility but reduces the Sharpe ratio.

4.3 Performance During Momentum Crash

Overall, the augmented value with the significant momentum anomalies improves the risk-adjusted returns. In addition, the augmented values for momentum results in reduced standard deviations for almost all momentum anomalies. According to Figure 1, value anomalies help momentum anomalies during the momentum crash, as explained by Daniel and Moskowitz (2016). According to Daniel and Moskowitz (2016), the low momentum portfolio outperforms the high momentum portfolio during panic or distress in the market. This results in underperformance of momentum anomalies after a crash, such as in the great depression, or the financial crisis of 2008-2009. Figure 1 identifies some market distresses by identifying the lowest point of events, such as Black Monday (October 1987), the dot-com boom (March 2002), global financial crisis (March 2009), and COVID-19 (March 2020). COVID-19 is the most recent market

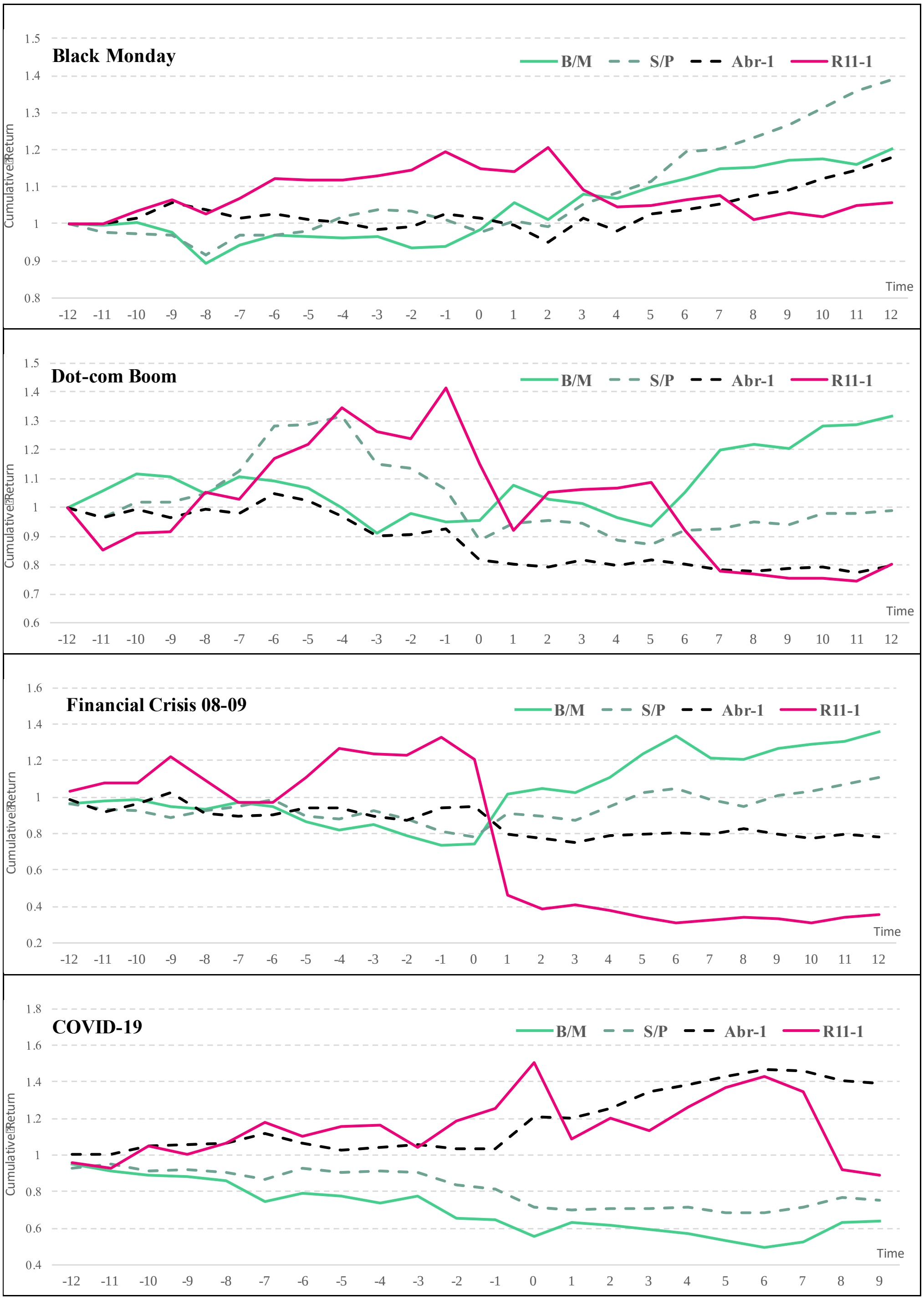

Figure 1 Value and Momentum during Big Market Drop

Note: This figure shows the cumulative returns of B/M, S/P, Abr-1, and R11-1 during four turbulent markets. The time period is one year before and after the lowest point of the market.

panic, when stock markets in many countries reacted negatively to the pandemic, according to Khanthavit (2020). Figure 1 shows examples of the cumulative returns of BM, S/P, Abr-1, and R11-1. The windows of the plots are one year before and after the identified months.

Before Black Monday, R11-1 looked to be the best-performing strategy. However, B/M and S/P outperformed after the crash, which helped the momentum anomalies. During the Dot-com Boom, R11-1 also was the best performing anomaly before the event, while Abr-1 was the laggard performer before the crash. However, the same pattern emerged after the crash. Both momentum anomalies underperformed after the crash, while B/M and S/P were great performers after the crash, which helped the momentum anomalies. During the Financial Crisis 08-09, R11-1 was again the best performing anomaly before and the worst-performing anomaly after the crash. R11-1 helped the value anomalies before the crash, but the value anomalies helped R11-1 after the crash. The Abr-1 did not look to be in line with R11-1, but followed B/M and S/P more. Before the COVID-19 crash, R11-1 and Abr-1 were the best performers, with value anomalies lagging. R11-1 had a significant drop during the crash and did not recover much when compared to Abr-1, B/M, and S/P, which were more stable afterward.

Overall, though most of the momentum anomalies have higher average monthly returns than the value anomalies, according to Table 3 and Table 4. Value anomalies helped momentum during the momentum crashes. B/M and S/P outperformed R11-1 and Abr-1 during Black Monday, the dot-com boom, and global financial crisis. The most pronounced effect was during the financial crisis of 2008 and 2009. However, B/M and S/P have underperformed R11-1 and Abr-1 during COVID-19. During the COVID-19 period, there is little sign of a momentum crash when value anomalies underperformed during COVID 19. Lastly, value and momentum anomalies exhibit negative correlations during these extreme market events, as shown in Figure 1. Figure 1 shows why momentum complements well with value during extreme events.

4.4 Empirical Asset Pricing Models

Table 5 and Table 6 use the empirical asset pricing models of AQ (Hou et al., 2021), FF5 (Fama and French, 2015), and FF6 (Fama and French 2018), to explain the augmented value with momentum portfolios. Hou et al. (2021) and Hou, Xue, and Zhang 2015 argue that the profitability factor (ROE) and investment factor (I/A) in the AQ model can explain the value anomaly. On the other hand, the HML factor in FF5 and FF6 can help to explain the value anomaly since it is mainly constructed from the B/M ratio. The AQ model also performs well in explaining momentum anomalies. FF6 contains the momentum

Table 5 The Augmented B/M with Momentum and Empirical Asset Pricing Models

	:SUE-1	:Abr-1	:Abr-6	:R11-1	:R6-1	:R6-6	:I-Mom
α_{AQ} (50:50)	0.0013	0.0042	0.0028	0.0011	0.0006	0.0013	0.0008
α_{FF5} (50:50)	0.0017	0.0038	0.0020	0.0061	0.0034	0.0046	0.0016
α_{FF6} (50:50)	0.0020	0.0044	0.0027	0.0021	0.0002	0.0019	0.0012
t_{AQ}(50:50)	1.4816	4.0974	3.2542	0.8338	0.3911	1.1624	0.8438
t_{FF5} (50:50)	2.4171	4.4012	2.8216	4.8085	2.5768	4.6775	2.1053
t_{FF6} (50:50)	2.7738	4.9872	3.7901	2.6782	0.1439	2.6615	1.6238
AR^2_{AQ}(50:50)	0.3237	0.3508	0.4643	0.2604	0.1960	0.2701	0.3906
AR^2_{FF5} (50:50)	0.4361	0.4199	0.5367	0.1866	0.2152	0.2690	0.4965
AR^2_{FF6} (50:50)	0.4404	0.4322	0.5607	0.6960	0.5151	0.6020	0.5027

Note: This table gives α's, t-statistics, and adjusted R^2 from AQ, FF5, and FF6 models of each augmented B/M with the momentum returns.

factor (UMD), while the FF5 factor model does not. Therefore, it is expected that FF6 is better able to explain the augmented value with momentum portfolios, since it contains both value and momentum factors. Table 5 uses B/M as a value anomaly, while Table 6 uses S/P as a value anomaly when constructing the augmented value with momentum portfolios.

The α's from the AQ model are not significant for all augmented B/M with momentum portfolios except those using Abr-1 (absolute t-statistics of 4.0974) and Abr-6 (absolute t-statistics of 3.2542) according to Table 5. Similarly to Hou et al. (2021), this study uses the number of significant α's based on the 0.1 level. This can translate to having an absolute t-statistic of 1.64. There are two significant α's for the AQ model. On the other hand, there are seven, and five significant α's for the FF5 and FF6 models, respectively. Therefore, the AQ model outperforms the FF5 and FF6 models using the number of significant α's. When considering the performance using the adjusted R^2, FF6 outperforms both FF5 and AQ. For example, the adjusted R^2 of FF6, FF5, and AQ for the augmented B/M with R11-1 are 0.6960, 0.1866, and 0.2604, respectively. Again, this is because FF6 contains both value and momentum factors, resulting in a better explanation of the augmented value with momentum. Removing the momentum factor from FF6, provides FF5. This allows for a comparison of FF5 and AQ, which contains the same number of five factors. The FF5 model still outperforms the AQ model as the adjusted R^2 is more in 5 out of

Table 6 The Augmented S/P with Momentum and Empirical Asset Pricing Models

	:SUE-1	:Abr-1	:Abr-6	:R11-1	:R6-1	:R6-6	:I-Mom
α_{AQ} (50:50)	-0.0001	0.0028	0.0013	-0.0003	-0.0009	-0.0002	-0.0007
α_{FF5} (50:50)	0.0012	0.0033	0.0015	0.0056	0.0029	0.0041	0.0011
α_{FF6} (50:50)	0.0005	0.0028	0.0011	0.0006	-0.0014	0.0004	-0.0003
t_{AQ}(50:50)	-0.1609	2.6029	1.4468	-0.2051	-0.5299	-0.1379	-0.6003
t_{FF5} (50:50)	1.4954	3.7182	2.0154	3.5570	1.8971	3.3150	1.1466
t_{FF6} (50:50)	0.5985	3.1612	1.5263	0.6082	-1.2567	0.5148	-0.3253
AR^2_{AQ}(50:50)	0.3370	0.2550	0.3278	0.2905	0.2099	0.2760	0.2762
AR^2_{FF5} (50:50)	0.3637	0.3477	0.4588	0.1181	0.1489	0.1587	0.3487
AR^2_{FF6} (50:50)	0.3955	0.3587	0.4657	0.6842	0.5705	0.6263	0.4347

Note: This table gives α's, t-statistics, and adjusted R^2 from AQ, FF5, and FF6 models of each augmented S/P with the momentum returns.

the 7 portfolios. Overall, the results are mixed between the Fama-French models and the AQ model. AQ provides a better explanation in terms of α's while FF6 outperforms when using the adjusted R^2.

Table 6 reports how the AQ, FF5, and FF6 models explain the augmented S/P with momentum portfolios. Similar results happen for the S/P augmented with momentum. There is one significant α for the AQ model using the number of significant α's based on the 0.1 level. There are five and one significant α's for the FF5 and FF6 models, respectively. Therefore, the performance of AQ is even with FF6, as they have the same number of significant α's. FF5 underperforms since it gives the highest number of significant α's for the augmented S/P with momentum portfolios. However, the FF6 model again outperforms when using the adjusted R^2. For example, the adjusted R^2 values for the augmented S/P with SUE-1 using AQ, FF5, and FF6 are 0.3370, 0.3637, and 0.3955, respectively. Again, this is due to the inclusion of the momentum factor (UMD) in the FF6. By removing the UMD factor, FF6 becomes FF5. The results between AQ and FF5 are mixed for the adjusted R^2. For example, the adjusted R^2 values for AQ and FF5 are 0.3370 and 0.3637, respectively, for the augmented S/P with R11-1. However, the adjusted R^2 for the AQ and the FF5 are 0.2905 and 0.1181, respectively, for the augmented S/P with R11-1. AQ has higher adjusted R^2 values for 4 out of 7 of the anomalies, when compared to FF5.

Overall, the performance of the asset pricing models AQ, FF5, and FF6, are mixed according to Table 5 and Table 6. In terms of the number of significant α's, AQ is the leading model. Using the adjusted R^2 values, the FF6 captures the augmented portfolios better than the AQ and the FF5.

5. CONCLUSIONS AND DISCUSSION

This study explored value augmented with momentum using various variables as indicators. It shows that value (using B/M and S/P) when augmented with significant anomalies of significant momentum portfolios (SUE-1, Abr-1, Abr-6, R11-1, R6-1, R6-6, and I-Mom) outperform the pure value, both in terms of average and the risk-adjusted return. The momentum anomalies also increase their risk-adjusted returns when coupled with different value anomalies.

The negative correlations between value and momentum anomalies help to explain the increased performances. Moreover, value strategy helps during momentum crashes, as discussed in Daniel and Moskowitz (2016). The most pronounced crash period was during the financial crisis of 2008-2009, when momentum underperformed. By implementing value with momentum, the strategy decreases volatility across each value and momentum anomaly.

The study shows how different anomalies can be augmented and improve performance with a suitable risk profile. It opens doors for other studies to find other anomaly combinations. At the same time, practical portfolio investment managers and investors can learn from this augmented strategy, constructing their portfolios accordingly. They can allocate their fund using different anomalies instead of sticking with only one strategy. The anomaly allocation looks more like a sound investment philosophy. The allocation of anomalies can be thought of similarly to asset class allocations.

This study also includes the empirical asset pricing models such as the augmented-q factor (AQ), the Fama-French five-factor (FF5), and Fama-French six-factor (FF6) models to explain value portfolios when augmented with momentum portfolios. The performance results for explaining the portfolios is mixed. The AQ model outperforms the FF5 and the FF6 using the number of significant α's as criteria. However, the FF6 model outperforms when using the adjusted R^2.

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