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A better model? Testing of Fama and French six-factor model in Pakistan

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Original Paper

A Better Model? Testing of Fama and French Six-factor Model in Pakistan

Mehak Younus

Abstract This study examines the performance of the Fama and French six-factor model and the alternative six-factor model in explaining anomalous return patterns using a broad sample of the Pakistani stock market from 2000 to 2017. This study is the first to test the applicability of these models in Pakistan and their performance in explaining anomalous returns. There are 11 anomalies taken, which proved to be significant in the Pakistani market. The GRS test is used with other time-series measures to check the power of the given models in explaining one-way sorted quintile portfolios. The results reveal that both models provide an incomplete description of anomalous returns. However, the six-factor model seems to be dominant with no major exception as it can explain 5 out of 11 anomalous portfolios returns, while the alternative model can explain four anomalies. The findings recommend that investors use the six-factor model because of its dominancy. It further recommends the investors about how they can maximize their returns by taking a long and short position in anomalous portfolios. Lastly, it is suggested to search for a better model to explain Pakistani stocks returns and capture anomalous patterns.

Keywords Asset pricing, Factor models, Six-factor model, Pakistani stock market, GRS test

1 Introduction

Starting with the work of Markowitz (1968) on asset allocation and asset returns, Sharpe (1964) studied the relationship between the expected return of an individual asset and market risk; hence, the concept of the Capital Asset Pricing Model (CAPM) emerged. Lintner (1975) refined Sharpes work by changing the properties of the formula. Fama (1970) explained the limitation of this model by introducing the Efficient Market Hypothesis which states that equity prices reflect all the available information if equity returns are obtained based

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on parameters used in CAPM. It further states that the additional information adjusts with equity returns due to additional market risk. However, arbitrage opportunities exist in a real equity market, so an equity market is not necessarily efficient in reflecting all available information. This hypothesis indicated the limitation of CAPM for not capturing the inclusion of other factors in measuring equity return and raised a question on the validity of this model. Next to *CAPM*, Arbitrage Pricing Theory (APT) was introduced by Ross in 1976. This theory explained the effect of multiple factors on equity returns and concluded that it is not just one factor that brings the variation in equity returns; the variation is due to multiple factors (macroeconomic factors). Meanwhile, other researchers documented the effect of different anomalies in bringing variation in the cross-sectional returns and rejected *CAPM* in fully explaining the cross-sectional returns Stattman (1980); Banz (1981); Basu (1983); Bhandari (1988). In response to these empirical rejections, Fama and French (1992) made the most influential investigation by rejecting market beta β and declared that size and book-to-market are better in capturing variation in returns. Since these revelations, finance experts have been looking for a pricing model that captures the maximum variation in the average returns of stocks. This quest led to the development of innumerable pricing models. However, few of them received recognition in both academia and real-world. One model that received recognition in the early 90s was Fama and French (1993) three-factor model (FF3).

Fama and French (1993) expanded the CAPM model with size (Small minus Big-SMB) and value (High minus Low-HML) factors. This model received both acclamation and criticism. Carhart (1997) later expanded the Fama-French's three-factor model with a momentum (Up minus Down-UMD) factor. Over the period, several researchers empirically rejected these models for explaining anomalous return patterns. To address these rejections, Fama and French (2015) expanded their previous model with investment (Conservative minus Aggressive-CMA) and profitability (Robust minus Weak-RMW) factors. They tested this model in the developed markets. Fama and French (2018) recently introduced a six-factor model $FF6_{OP}$ with an addition of momentum (WML) in their five-factor model (FF5). They also developed an alternative six-factor model $FF6_{CP}$ by replacing operating with cash profitability and found that this alternative model performed well in the U.S. market under all the performance metrics.

This study is an out-of-sample test of the Fama-Frenchs $FF6_{OP}$ and $FF6_{CP}$ model. I tested these models in capturing the anomalous return patterns in the Pakistani stock market (PSX) by taking 11 anomalies in a sample. These anomalies are from different categories, one is from trading friction, one is from intangible, three are from profitability, three are from valueversus-growth, and three are from investment. These anomalies passed the significance criteria of t 1.96. It is known that different markets have different anomalies, and the significance of a factor/model is diverse among different markets (Jacobs 2016). For instance, *HML* is a redundant factor in the U.S. market, and *CMA* is redundant in the Chinese market (Guo et al 2017). Also, the *WML* factor performs well in

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the developed markets but is less noticeable in Asian developing markets (Asness et al (2013); Lin (2017)).

There are several studies based on the role of Fama and French models in explaining anomalies in the U.S. and major developed and developing markets, which is according to Andrew Karolyi (2016), have a home and a foreign bias. All these markets are well integrated and yield similar results. Contrary to this, few studies are on non-developed markets though these markets also hold importance for investors. They hold different characteristics and have different dynamics than the well-integrated markets. Some of these markets have been studied by Zaremba and Czapkiewicz (2017); Lin (2017); Foye (2018); Hanauer (2020), yet the empirical evidence is scant. Therefore, this study is needed because the question of most suitable asset pricing model for a particular market is vital for academicians and practitioners. It is because the investors can rely on local, not international, asset pricing factors. Hence, this study provides compelling results from a fresh sample of Pakistans equities data. Moreover, no attempt has been made to test the $FF6_{OP}$ and $FF6_{CP}$ model in the PSX market. Therefore, an out of-sample study describes the best applicability of these models, specifically in the context of emerging and frontier markets.

My focus is on the PSX because it holds the typical characteristics of an emerging market though it has recently been reclassified to a frontier market. Khwaja and Mian (2005) found that this market has a significant share of small and less profitable firms having moderate to high investment levels. It offers high returns with high volatility in these returns, high trading volume, and low market capitalization. Ali et al (2021) found that Pakistani financial firms share unique liquidity and active participation characteristics. As said earlier, developing and frontier markets have different dynamics than the developed markets; hence, the characteristics of PSX are different from the characteristic of developed and major emerging markets. Besides these dynamics, this market is essential for local and foreign investors to allocate their funds. This market experienced increased foreign ownership of shares during Covid-19, where other markets faced a setback. It was also declared the best Asian market during this challenging time of Covid-19 (PSX 2022). Still, there is limited research on this market. Hence, this study investigates if the considered promising models work well in explaining anomalous patterns in the Pakistani market.

The remaining paper is structured as follows: Section 2 provides the study's theoretical framework. Section 3 provides a review of existing literature. Section 4 discusses a detailed methodology of factors construction, anomalies portfolios construction, and testing measures. Section 5 provides empirical findings of this study and how previous research findings support or contradict this studys findings. Section 6 concludes the study with the practical implications of the findings.

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2 Theoretical Framework

In the mid of 1900s, the groundwork for a theory related to stock price behavior came to light. The main principle of an investment theory is never to put all the eggs in a single basket. Hence, the investors know that they must act rationally by investing in a diversified portfolio. They must have an extra unit of insurance for an extra unit of risk. Markowitz (1968) joined all the above points and came up with a mathematical approach of portfolio selection based on a Mean-Varian (M-V) approach, which later became the base of the Modern Portfolio Theory. The Markowitz Portfolio Selection theory shows the power and the importance of diversification by using an MV approach to choose their efficient portfolio from the available set of securities to optimize the earnings in a single period. Hence, a risk-averse investor chooses an optimal portfolio that maximizes his/her return with minimal variance in a single period. Plotting all these choices of efficient portfolios results in a hyperbola line, and this hyperbola line on which all the efficient portfolios sit is known as the efficient frontier. A rational investor will try to move to the Northside on this frontier and choose a portfolio that generates a desirable return against his/her risk tolerance level.

It is a remarkable work of Markowitz. However, the problem with this is being a Single Index Model as when it was introduced, it was not easy to calculate the variance-covariance of all the assets. Several researchers then worked on this theory, and later on, *CAPM* emerged with its added assumptions of homogeneous expectations, market equilibrium, and risk-free rate for borrowing/lending. With these assumptions, a new M-V efficient frontier came into light. All the investors invest in portfolio M (value-weighted market portfolio of all risky assets) and a risk-free asset, together, as all investors are homogenous. Based on this, the expected return on an asset can be expressed as;

$$E(R_i) = R_f + \beta_f[E(R_m) - R_f] \tag{1}$$

In the above *CAPM* equation:$E(R_i)$] is the expected return on risky asset, R_f is the riskfree rate, $E(R_m)$ is the expected market return, $R_m - R_f$ is the risk premium, and β is the movement of the assets return sensitive to the movement of the market return, it is expressed as;

$$\beta = \frac{cov(R_i R_m)}{\sigma^2(R_m)} \tag{2}$$

Where $cov(R_i R_m)$ is the covariance between the asset and market return, and $\sigma^2(R_m)$ is the variance of the market return.

As previously stated, *CAPM* has received many criticisms, and many authors reported the poor performance of this model. A strong response was made by Ross (2013), who introduced Arbitrage Pricing Theory. This theory states that arbitrage opportunities do not continue for long in a well-functioning market as prices adjust quickly once these opportunities are exploited. This theory

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further stated that there are enough assets in the market to diversify the unsystematic risk. The variation in asset returns is due to the systematic risk of n factors. The expected return on an asset can be written as;

$$E(R_i) = R_f + \beta_{i,1}\lambda_1 + \beta_{i,2}\lambda_2 + ... + \beta_{i,n}\lambda_n \tag{3}$$

In the above equation:$E(R_i)$] is the expected return on risky asset,R_f is the risk-free rate,$\beta_{i,1}$ is the movement of the assets return sensitive to the movement of the risk factor one, and λ_1 is the risk premium for risk factor one.
Some researchers were busy testing and developing the models to predict future prices of stocks, and others were exploring the concept of efficient markets. The primary assumption is that the market is rational and friction-free. Fama (1970) theorized that all the stocks prices in the market always fully reflect all available information. Several researchers tested for the efficient market theory and found mixed results. Other researchers started reporting the lack of *CAPM* in explaining inconsistency in the pattern of stock prices; this was when the concept of anomalies came into existence. Fama and French (2008) defined anomaly as a return pattern that the chosen asset pricing model cannot explain. Since the *CAPM* failed to accommodate the proposed anomalies, other models emerged.

3 Literature review

3.1 Evolvement of asset pricing models

Existing literature highlighted many anomalies that brought variation in the stock returns and questioned the credibility of *CAPM*. Stattman (1980) studied an anomaly, book-to-market equity (B/M), and found that B/M and stock return positively relate in the U.S. market. In Banz (1981) found that size brings a most prominent effect on the stock returns. He found that the size represented by market equity explains the variation in the cross-section returns of stocks. His study concluded that companies with low market equity have high average returns, and companies with high market equity have low average returns given their β estimates. Basu (1983) studied the relationship of β, size, and earning-to-price ratio (E/P) with the U.S. stock returns and concluded that E/P helps explain the U.S. stocks returns. Barr Rosenberg and Lanstein (1998) supported the findings of Stattman by concluding that both B/M and U.S. stock returns have a positive association. Another anomaly explaining the stock returns was of leverage. Bhandari (1988) studied the relationship of β market equity, and leverage with the stock returns and concluded that leverage and stock returns hold a positive association. Following these studies of U.S. stocks market, Chan et al (1991) studied the relationship of B/M and stock returns in the Japanese stock market and concluded that B/M plays a substantial role in explaining the variation in stock returns. Based on these studies, it can be said that all these variables scale the prices of stocks in their way. However, it can be expected that some of these variables are redundant in explaining the variation in stock

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returns.

Fama and French (1992) studied the combined effect of β, size, leverage, E/P, and B/M on cross-sectional stocks' expected returns in the U.S. market following the above claims. Previously, Fama and MacBeth (1973) found that during the pre-1969 period, there was a positive association between β and stock returns. However, this study found that this relationship disappeared from 1963 to 1990 even when β alone was taken to explain the stock returns. This relationship was also weak from 1941 to 1990. Thus, this study proved that the tests do not support the findings of *CAPM* that β and stock returns share a positive relation. In addition, size, leverage,E/P , and B/M share a strong univariate relation with stock returns. In multivariate testing, a negative association of stock returns with size and a positive association with B/M persists in inclusion with other variables. The bottom-line results of this study proved that β does not help in explaining the variation in stock returns. In addition, size and B/M are the two proxies of risk if assets are priced rationally. Also, a combination of B/M and size absorb the effect of B/M and leverage in explaining the stock returns from 1963 to 1990. Thus, factor models emerged in response to the empirical failure of *CAPM*.

Following Fama and French (1993), Carhart (1997) introduced a four-factor model extending the FF3 model with momentum. He compared his model with CAPM and FF3 and tested these models using short and long intervals of past returns. Under short intervals, he found that the Carhart model explains a considerable time-series variation in the stock returns. After Carhart, many other authors claimed that the FF3 model does not explain variation related to profitability and investment in the stock returns as the valuation theory states that B/M, expected investment, and expected profitability explains the stock returns as stock returns are related to these variables (Haugen and Baker 1996; Titman et al 2004; Fama and French 2006, 2008). These claims led Fama and French (2015) to extend their FF3 model to a FF5 model. They also observed patterns in stock returns related to these five factors, but the GRS test rejected this model in capturing these patterns. It was also suggested that value is a redundant factor since other remaining factors fully capture its effect in explaining stock returns, especially profitability and investment factors.

3.2 Recent developments in asset pricing models

Meanwhile, some new models emerged that gained popularity and were tested in the U.S. market (Hou et al 2017; Stambaugh and Yuan 2017; Barillas et al 2020; Daniel et al 2020). One of these models is a q-factor model developed by Hou et al (2017). They introduced this model when FF3 failed to accommodate a wide range of anomalies and proved that the q-factor model successfully accommodates many but not all anomalies. The second model that is also recognized is the mispricing model of Stambaugh and Yuan (2017). They tested

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their models to accommodate a set of anomalies by taking FF3, FF5, and q-factor models in the horserace and found their model to be the best performer. Fama and French (2018) recently developed $FF6_{OP}$ and $FF6_{CP}$ models. They tested all their models using the maximum squared Sharpe ratio and found their alternative six-factor model to be the winner.

3.3 Empirical Testing of Fama and French Six-Factor Model

Chai et al (2019) conducted a study in U.S. and Australian markets using FF5 and $FF6_{CP}$ models. They found that the six-factor model is a reasonable choice for both U.S. and Australia as the additional factor of momentum plays a significant role in the presence of other factors. Fletcher (2018) tested the performance of old and new pricing models in the U.K. market and found the six-factor model of Fama and French to be dominant in explaining the U.K. stocks returns. Hou et al (2019) conducted a study in the U.S. market and tested which model is best at subsuming the factors of other models. They compared their -factor model with the mispricing model of Stambaugh and Yuan (2017) and Fama and Frenchs five- and six-factor model (2015, 2018). They found their model to be dominant in subsuming the factors of competing models. Barillas et al (2020) tested eight models in the U.S. market, including Hou et al (2017) q-factor model; altered q-factor model, He et al (2017) two-factor model; Frazzini and Pedersen (2014) extended $CAPM$ model; Stambaugh and Yuan (2017) mispricing model; Fama and Frecnh (2015) five-factor model (replaced operating with cash profitability); Fama and French (2015) alternative-six factor model; and altered six-factor model (replaced regular value factor with Asness and Frazzini (2013) value factor). They found the altered six-factor model to be the dominant model. Zaremba et al (2021) conducted a study on frontier markets and tested the performance of seven models, including $CAPM$ model, Carhart, q-factor, FF3, FF5, $FF6_{OP}$, and Barillas and Shanken model. They found Carhart mode to be the dominant one in frontier markets.

It is evident from the literature above that FF6 is mainly tested in the developed markets, and authors have mostly tested the FF5 model in the emerging markets (Cakici 2015; Zaremba and Czapkiewicz 2017; Elliot et al 2018; Kubota and Takehara 2018; Jiao and Lilti 2017; Lin 2017; Belimam et al 2018; Foye 2018). There is a clear gap of FF6 not being tested in the emerging and frontier markets and never in the PSX. This study, therefore, fills this gap by contributing to the overall literature of asset pricing and mainly contributing to the literature of recent developments in asset pricing in non-developed markets.

4 Data and analysis

My dataset includes stocks traded at PSX from January 2000 to December 2017. I included both active and dead firms. All accounting and financial data are downloaded from Thomson DataStream (TDS). I used annual accounting figures as quarterly reporting is not standard in Pakistan. After collecting the raw dataset, I applied a detailed filtration process before and after downloading

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the data. Before downloading it, I filtered the firms using static information. Only those firms were chosen that had instrument type EQUITY, geographical code of PAKISTAN, and currency code of PR, remaining firms were removed. I further checked the timestamp, and all those firms were removed whose data was constant since the start of the sample period. After this, I downloaded the data and filtered the data further using Ince and Porter (2006) guidelines. I checked the stationarity and trailing ends of all the variables and dropped firms having this issue. Next to this, I cleaned for extreme observations;

$$R_t monthly(daily) > 800\%(200\%)$$

I further checked for infrequent trading and retained those firms that traded for at least three or more days in a month. Hence, the final sample included 290 firms. Moving onto filtration in the sorting process, I dropped the firms from the yearly sorts that had empty data. Following are the conditions for including the firms in yearly sorts, otherwise dropped;

$$BEME > 0$$
$$-0.5 < INV < 1$$
$$300\% < Prof < 300\%$$

The above conditions of *Inv* and *Prof* are not applied to remove the data errors but are mainly for avoiding the inclusion of an observation that is unlikely to occur during normal circumstances. For example, a condition of removing stocks having *Inv* less than -0.5 means that the firm lost half of its assets in a given year which seems unlikely to happen (Sundqvist et al 2017).

4.1 Construction of factors

$$\begin{aligned} r_{i,t} = \alpha_{iFF6op} + \beta_{i,MKT}MKT_t + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t \\ + \beta_{i,RMW}RMW_{OP} + \beta_{iCMA}CMA_t + \beta_{i,WML}WML_t + error_{i,t} \end{aligned} \tag{4}$$

$$\begin{aligned} R_{i,t} = \alpha_{iFF6_{OP}} + \beta_{i,MKT}MKT_t + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t \\ + \beta_{i,RMW}RMW_{CP} + \beta_{iCMA}CMA_t + \beta_{i,WML}WML_t + error_{i,t} \end{aligned} \tag{5}$$

The factors of Fama and French which includes- Market Mk_t, Size (SMB), Value(HML), Investment(CMA), Profitability (both operating and cash-RMW_{OP} and RMW_{CP}, and Momentum (WML), are constructed using a traditional approach of 2 * 3 sorts.

Size at the June of each year t, was calculated as P at the end of December of year $t-1$ multiplied by *NOSH* at the end of December of year $t-1$, which forms the market capitalization, also known as market equity of a stock denoted by *ME*. *ME* is taken as a measure of size. *Size* was divided into two groups- Small (denoted by S) and Big (denoted by B) using a median of the series (ordered ascendingly) each year t as a breakpoint. *SMB* is calculated as an average of $SMB_{BE/ME}$, SMB_{OP}, and SMB_{INV}. Here, $SMB_{BE/ME}$ is the monthly average returns of three small value portfolios minus the monthly

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average returns of three big value portfolios. SMB_{OP} is the monthly average returns of three small profitability portfolios minus the monthly average returns of three big profitability portfolios. SMB_{INV} is the monthly average returns of three small investment portfolios minus the monthly average returns of three big investment portfolios.

Value at the end of each year t was calculated by dividing book equity (denoted by BE) of fiscal year t with market equity (calculated above) of the end of December $t-1$. Here the BA is calculated as the total assets (TA) of fiscal year $t-1$ minus the total liabilities (TL) of fiscal year $t-1$. At the end of each year t, *value*(ordered ascendingly) was then divided into three groups using 30th and 70th percentiles as breakpoints. The stocks falling in the first 30th percentile are Low-value stocks (denoted by L), stocks falling in the middle 40th percentile are Neutral value stocks (denoted by N), and the last 30th percentile stocks are High-value stocks (denoted by H). Following Fama and French (2015), I constructed *HML* from 2 * 3 sorts by interacting size (S and B) with value (L, N, and H). This intersection formed six size-value portfolios- S/L,S/N,S/H, B/L, B/N and B/H. I then calculated monthly sorted portfolios returns from July of year t to the end of year $t-1$ by value-weighting (VW) the portfolios[1] These sorted VW portfolio returns are then used to calculate the actual factor returns. *HML* is calculated as monthly average returns of two high-value portfolios (S/A and B/H) minus monthly average returns of two low-value portfolios (S/L and B/L).

Investment at the end of each year t was calculated by dividing the annual change in TA with a lagged TA[2] At the end of each year t, Investment (ordered ascendingly) was then divided into three groups using 30th and 70th percentiles as breakpoints. The stocks falling in the first 30th percentile are Conservative stocks (denoted by C), stocks falling in the middle 40th percentile are Neutral stocks (denoted by N), and the last 30th percentile stocks are Aggressive stocks (denoted by A). Following Fama and French (2015), I constructed *CMA* from 2 * 3 sorts by interacting size (S and B) with Investment (C, N, and A). This intersection formed six size-investment portfolios- S/C,S/N,S/A, B/C,B/N, B/A. *CMA* is calculated as monthly average returns of two conservative investment portfolios (S/C and B/C) minus monthly average returns of two aggressive in-

[1] Value weighted returns are calculated according to stocks market cap by using the following formula

$$Value - weighted\, return\, on\, stock_{i,t} \\ = \frac{simple\, average\, return\, of\, stock_{i,t} \, * \, Market\, capitalization\, of\, stock_{i,t-1}}{Market\, capitalization\, of\, portfolio_{t-1}} \quad (6)$$

[2] Investment in FF is calculated using the following formula

$$\Delta\, in\, TA = \frac{TA_{t-1} - TA_{t-2}}{TA_{t-2}} \quad (7)$$

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vestment portfolios (S/A and B/A).

Following Fama and French (2018), I have constructed two versions of profitability based on operating and cash profit. **Operating profitability** at the end of each year t is measured with the data in year $t-1$. It is *revenue* minus *minus cost of goods sold* (0 if missing) minus *selling, general and administrative expenses* (0 if missing) minus *interest expense* (0 if missing) divided by *BE*. It is required to have a non-missing value of at least one of the expenses. At the end of each year t, *Operating profitability* (ordered ascendingly) was then divided into three groups using 30th and 70th percentiles as breakpoints. The stocks falling in the first 30th percentile are Weak stocks (denoted by W), stocks falling in the middle 40th percentile are Neutral stocks (denoted by N), and the last 30th percentile stocks are Robust stocks (denoted by R). Following Fama and French (2015), I constructed RMW_{OP} from 2 * 3 sorts by interacting size (S and B) with profitability (W, N, and R). This intersection formed six size-OP portfolios- S/W_{OP},S/N_{OP},S/R_{OP}, B/W_{OP},B/N_{OP}, B/R_{OP}. RMW_{OP} is calculated as monthly average returns of two robust portfolios (S/R_{OP} *and* B/R_{OP}) minus monthly average returns of two weak portfolios (S/W_{OP} *and* B/W_{OP}).

In the second version of profitability, **cash profitability** is computed for year t as operating profit (computed above) minus accruals with the data of year $t-1$. Accruals are calculated as a change in *receivables* (0 if missing) plus change in *prepaid expense* (0 if missing) minus change in *accounts payable*(0 if missing) minus change in *total inventory* (0 if missing) minus change in *deferred income* (0 if missing) minus change in *accrued expense* (0 if missing) . This change is calculated from $t-2$ to $t-1$. After following the same sorting process, six size-CP portfolios are formed- S/W_{CP},S/N_{CP},S/R_{CP}, B/W_{CP},B/N_{CP}, B/R_{CP}. RMW_{CP} is calculated as monthly average returns of two robust portfolios ($S/R_{CP} and B/R_{CP}$) minus monthly average returns of two weak portfolios ($S/W_{CP} and B/W_{CP}$).

Momentum is measured as cumulative returns from $t-12$ to $t-2$. Momentum (ordered ascendingly) was then divided into three groups using 30th and 70th percentiles as breakpoints at the end of each month. The stocks falling in the first 30th percentile are Loser stocks (denoted by L), stocks falling in the middle 40th percentile are Neutral stocks (denoted by N), and the last 30th percentile stocks are Winner stocks (denoted by W). Following Fama and French (2015), I constructed *WML* from 2 * 3 sorts by interacting size (S and B) with value (L, N, and W). This intersection formed six size-value portfolios- *S/L*,*S/N*,*S/W*, *B/L*,*B/N*, *B/W*. *WML* is calculated as monthly average returns of two winner portfolios (S/W and B/W) minus monthly average returns of two loser portfolios (S/L and B/L).

Market is calculated by taking a difference of monthly return on market index and the one-month risk-free rate.

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Table 1: : Factors Construction Details

Variables	**Grouping Breakpoints**	**Factors**
Size	Yearly median	SMB=$\frac{SMB_{BE/ME}+SMB_{OP}+SMP_{INV}}{3}$ where,
		$SMB_{BE/ME}=\frac{S/L+S/N+S/H-(B/L+B/N+B/H}{3}$
		$SMB_{OP}=\frac{(S/W_{OP}+S/N_{OP}+S/R_{OP})-(S/W_{OP}+S/N_{OP}+S/R_{OP})}{3}$
		$SMB_{INV}=\frac{(S/C+S/N+S/A)-(B/C+B/N+B/A)}{3}$
BEME	Yearly 30th and 70th percentiles	HML=$\frac{(S/H+S/N+S/A)-(S/L+B/L)}{2}$
Operating profitability	Yearly 30th and 70th percentiles	$RMW_{OP}=\frac{(S/R_{OP}+B/R_{OP})-(S/W_{OP}+B/W_{OP})}{2}$
Investment	Yearly 30th and 70th percentiles	CMA=$\frac{(S/C+B/C)-(S/A+B/A)}{2}$
Cash profitability	Yearly 30th and 70th percentiles	$RMW_{CP}=\frac{(S/R_{CP}+B/R_{CP})-(S/W_{CP}+B/W_{CP})}{2}$
Momentum	Yearly 30th and 70th percentiles	WML=$\frac{(S/W+B/W)-(S/L+B/L)}{2}$

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4.2 Construction of Anomalous Portfolios

I tested 11 anomalies using annual accounting data. These anomalies were chosen based on data availability and their significance. The computation of anomaly variables is provided in the appendix. I constructed one-way sorted portfolios. Each anomaly portfolio was formed by grouping the firms into quintile portfolios. This sorting depended on the future returns relationship with a score on an anomaly.

Firm Size (mc) - I split stocks into quintiles at the end of each year t , based on the end of June market equity. Banz (1981) and Fama and French (1992) found a negative relationship between size and stock returns. Hence, I assign stock with a high mc value to a high quintile.

Operating Leverage (ol) - Following Novy-Marx (2011), I split stocks into quintiles at the end of each year t, based on the operating leverage. As per the literature, there is a positive relationship between operating leverage and stock returns. Hence, I assign stock with a high ol value to a low quintile.

Accruals (acc) I split stocks into quintiles at the end of each year t, based on accruals for the financial year ending $t-1$. Sloan (1996) found a negative relationship between accruals and stock returns. Hence, I assign stock with a high acc value to a high quintile.

Total Accruals (tacc) - I split stocks into quintiles at the end of each year t, based on total accruals. Richardson et al (2005) reported a negative relationship between total accruals and stock returns. Hence, I assign stock with a high tacc value to a high quintile.

Net Stock Issuance nsi **-** I split stocks into quintiles at the end of each year t, based on net stock issuance. Fama and French (2008) found a negative relationship between net stock issuance and stock returns. I assign negative nsi to quintile one and with nsi equal to 0 to quintile two. I divide the remaining stocks between the third, fourth, and fifth quintile (a stock having a high nsi value to a high quintile).

Book-to-market Equity (beme) - I split stocks into quintiles at the end of each year t, based on the book-to-market equity ratio. Basu (1983) and Fama and French (1992) found a positive relationship between this ratio and stock returns. Hence, I assign stock with a high beme value to a low quintile.

Cashflow-to-price (cf) - This anomaly was discovered by Lakonishok et al (1994). Based on the cashflow-to-price ratio, I split stocks into quintiles at the end of each year t. There is a positive relationship between this ratio and stock returns as per the literature. Hence, I assign stock with a high cf value to a low quintile. Note: All the stocks having negative cashflows were excluded.

Earnings-to-price (ep) - I split stocks into quintiles at the end of each year t, based on the earnings-to-price ratio. Following Basu (1983), who reported a negative relationship between this ratio and stock returns, I assign stock with a high ep value to a high quintile. Note: All stocks having negative earnings were excluded.

Gross Profitability Premium (gpp) - I split stocks into quintiles at the end of each year t, based on gross profitability premium for the financial year ending $t-1$. Novy-Marx (2013) found a positive relationship between gross profitability

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premium and stock returns. Hence, I assign stock with a high gpp value to a low quintile.
Gross Profit-to-assets (GptoTA) - I split stocks into quintiles at the end of each year t, based on gross profit-to-assets for the financial year ending $t-1$. Novy-Marx (2013) found a positive relationship between this ratio and stock returns. Hence, I assign stock with a high GptoTA value to a low quintile.
Operating Profits-to-lagged Equity (otle) - I split stocks into quintiles at the end of each year t, based on operating profits-to-lagged equity for the financial year ending $t-1$. Fama and French (2015) found a positive relationship between operating profits-to-lagged equity and stock returns. Hence, I assign stock with a high otle value to a low quintile.

4.3 Empirical Testing

For one-way sorted portfolios, I tested the performance of given models in explaining anomalous returns using the GRS tests F-statistic (Gibbons et al 1989). The H_0 of this test is that all the alphas of LHS portfolios are jointly zero in a given model. A lower value of this measure is desirable. Second, I used $A|\alpha|$, the average absolute alpha. A lower value of this measure is desirable. Third, I used $\frac{As^2}{A|\alpha|^2}$, a ratio of the average variance of alpha to the average squared alpha. alpha. A higher value of this measure is desirable. Fourth, I used $Sh^2(f)$, a maximum squared Sharpe ratio of the alphas of $Sh^2(\alpha)$ portfolios. A lower value of this measure is desirable. Fifth, I used $Sh^2(f)$, a maximum squared Sharpe ratio of factor(s). A higher value of this measure is desirable.

5 Results

Table 1 presents descriptive statistics of factor returns. It includes the mean, t-stat, and Sharpe ratio. SMB_{OP} produced the highest positive average return (1.64%), and the lowest positive return is of WML (0.03%). Both profitability and investment factors produced negative average returns. Besides this, MKt, SMB_{OP}, SMB_{CP}, and HML produced significant returns as the t-stat of these factors is greater than 1.96, and $RMW_{OP}$and RMW_{CP} are significant at 10% level as the t-stat is equal or greater than 1.65. However, CWA and WML returns are insignificant. As expected, the highest Sharpe ratio is of SMB_{OP}, and the lowest is of WML. I found a strong size and value effect. Fama and French (1993) found the value premium larger for small firms in the U.S. market, but it was missing in the Chinese market (Guo et al (2017)). My findings also support the phenomenon of Fama and French.

Table 2 presents the descriptive statistics of anomalous portfolios. It includes the mean and t-stat of high-minus-low (H-L) quintile portfolios. All these anomalies are significant at the 5% level as the t-stat of all H-L quintile portfolios is greater than 1.96. The mc H-L quintile portfolios average return is -3.80

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Table 2: Descriptive Statistics of Factors

	Mkt	SMBOP	SMBCP	HML	RMWOP	RMWCP	CMA	WML
Mean	1.36	1.64	1.63	1.35	-0.96	-1.32	-0.22	0.03
t-stat	2.47	3.08	3.03	2.23	-1.65	-1.79	-0.46	0.08
Shi	0.17	0.22	0.21	0.16	-0.12	-0.13	-0.03	0.01

Note: This table reports summary statistics for VW monthly returns of the factors in $FF6_{OP}$and $FF6_{CP}$ model. MKT,SMB_{OP} , SMB_{CP}, HML, RMW_{OP},$FF6_{CP}$ CMA, and WML, are the market, size, value, profitability, investment, and momentum factors in the FF models. The sample period is from January 2000 to December 2017 (204 months)

proving the size effect in Pakistan means small firms generate higher average returns than big firms. An investor can long small and short big stocks. This finding is consistent with the risk-return relationship. Small firms are considered a risk by the investors. To invest in a risky firm, investors demand a premium; therefore, small firms offer risk premiums in the form of higher returns. Ali et al (2021)) also proved this size effect in Pakistan. The *ol* H-L quintile portfolios average return is -1.09 indicating a leverage effect. An investor can long high *ol* and short low *ol* stocks. Bhandari (1988) found a positive relationship between leverage and stock returns, and my findings support this Bhandaris phenomenon of leveraged firms having higher risk tend to generate higher returns.

The acc H-L quintile portfolios average return is -1.73, -1.54 of nsi, and 1.21 of tacc. First two anomalies indicate an investment effect that firms with low investment tend to generate higher returns. Therefore, An investor can long low acc/nsi (high tacc) and short high acc/nsi (low tacc) stocks. Mohammad and Javid (2015) found acc significant and suggested the same investment strategy with an H-L decile return of -11.26%. My findings support the Sloan (1996) phenomenon that accrual shares a negative relationship with stock returns as accrual is connected to the non-cash earnings. An essential question for the practitioners is whether the earnings are based on real cashflows or accruals, which is merely an accounting practice. He proved that firms with low accruals generate real earnings, and firms with high accruals could be some accounting practice. Hence, stocks with low accruals earn higher average returns. Moving onto nsi, Ahmed and Kashif (2015) found nsi significant in two sub-sample periods and insignificant in one sub-sample period with a H-L quintile average return between -0.411 to -0.421.

The beme H-L quintile portfolios average return is -1.53 and -1.28 of ep. These results indicate a value effect that the value stocks generate higher returns than the growth stocks. Ali et al (2021) also proved the same effect in Pakistan with BEME taken as a measure of value. An investor can long high beme/ep and short low beme/ep stocks. Contrary to our result of ep, Ali et al (2021) found ep anomaly insignificant in the Pakistani market with a positive H-L quantile return of 0.06. The cf H-L quintile portfolios average return is 1.63. An investor can long low cf and short high cf stocks. Ali et al (2021) contradict my result in terms of significance only, not in the direction of average return. The GPtoTA H-L quintile portfolios average return is -1.40, -1.30 of

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gpp, and -1.80 of otle. These results indicate a profitability effect that firms having high profitability produce high average returns. An investor can long high *GPtoTA/gpp/otle* and short low *GPtoTA/gpp/otle* stocks. Ali et al (2021) also proved the profitability effect in Pakistan.

Table 3: Descriptive Statistics of Anomalous Factors

	mc	ol	acc	nsi	tacc	beme	ep	cf	GP to TA	gpp	otle
Mean	-3.8	-1.09	-1.73	-1.54	1.21	-1.53	-1.28	1.63	-1.4	-1.3	-1.8
t-stat	-4.85	-2.03	-2.31	-2.36	2.35	-2.59	-2.46	2.79	-2.2	-2.54	-2.96

Note: This table provides mean and t-values of high-minus-low quintiles of significant anomalous portfolios. mc is firm size. ol is operating leverage. acc is accruals. nsi is net stock issuance. tacc is total accruals. beme is book-to-market equity. ep is earning-to-price. cf is cashflow-to-price. otle is operating profit-to-lagged equity. gpp is gross profit premium. GPtoTA is gross profit-to-lagged equity. The sample period is from January 2000 to December 2017 (204 months).

Table 3 presents the correlation among factor returns. Both size factors hold a strong positive relationship. Similar is the case with profitability factors; both hold a strong positive relationship. Both size factors hold a positive relationship with HML and a negative relationship with *RMW* and *CMA*. It means small firms tend to have a higher *B/M* ratio, lower profitability, and higher investment. Moreover, the positive relationship of HML with CMA and negative with *B/M* indicates that the firms having high tend to be low profitable and low investment firms. It now makes sense that the *CMA* and *RMW* factors are negatively related to each other because firms with low profitability tend to invest less.

Table 4: Correlation Matrix of Factors

	SMB_{OP}	SMC_{OP}	HML	RMW_{OP}	RMW_{CP}	CMA	WML
SMB_{OP}	1						
SMC_{OP}	0.98	1					
HML	0.33	0.34	1				
RMW_{OP}	-0.43	-0.41	-0.54	1			
RMW_{CP}	-0.52	-0.51	-0.44	0.66	1		
CMA	-0.01	-0.02	0.07	-0.33	-0.2	1	
WML	0.07	0.09	0.01	0.15	0.05	-0.15	1

Note This table reports summary statistics for VW monthly returns of the factors in $FF6_{OP}$ and $FF6_{CP}$ model. MK_t, SMB_{OP}, SMB_{CP}, HML, RMW_{OP}, RMW_{CP}, CMA, and WML are the market, size, value, profitability, investment, and momentum factors in the FF models. The sample period is from January 2000 to December 2017 (204 months).

After checking the anomalous patterns and their effect in the Pakistani market, I tested if the chosen models could explain these anomalous returns. Table 4 presents the performance of both models in explaining univariate sorted portfolios. For mc quintile portfolios, the GRS test rejected both $FF6_{OP}$ and

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$FF6_{CP}$ in significantly explaining the firm size anomalous returns. While looking at other metrics, both the models secured the same position by obtaining the same value of $A|\alpha|$ and $Sh^2(\alpha)$. However, other metrics show the supremacy of $FF6_{OP}$ over the $FF6_{CP}$ model as this model obtained lower GRS statistic (5.576), a higher $\frac{As^2}{A|\alpha|^2}$ (0.182), and a higher $Sh^2(f)$ (0.305). The $Sh^2(f)$ value remains the same as it is a Sharpe ratio of the given models.The $Sh^2(f)$ value remains the same as it is a Sharpe ratio of the given models. For ol quintile portfolios, the GRS test rejected both $FF6_{OP}$ and $FF6_{CP}$ in significantly explaining the operating leverage anomalous returns. Both the models performed equally under $\frac{As^2}{A|\alpha|^2}$ and $Sh^2(\alpha)$. However, $FF6_{OP}$ again won over the $FF6_{CP}$ model by obtaining a lower GRS statistic (4.120) and a lower $A|\alpha|$ (0.015).
For acc quintile portfolios, the GRS rejected both $FF6_{OP}$ and $FF6_{CP}$ in providing a complete description of accrual anomalous returns. Both the models scored the exact value of $A|\alpha|$. Moreover, $FF6_{CP}$ dominated the $FF6_{OP}$ model by performing better in two metrics, while $FF6_{OP}$ performed better in one metric. The dominating model scored higher $\frac{As^2}{A|\alpha|^2}$ (0.287), and a lower $Sh^2(\alpha)$ (0.084), and $FF6_{OP}$ obtained lower GRS statistic (3.054).

For tacc quintile portfolios, the GRS rejected both $FF6_{OP}$ and $FF6_{CP}$ in explaining total accrual anomalous returns; however, the p-value is close to 5%. Both the models have the same values of $A|\alpha|$ and $Sh^2(\alpha)$. There is no clarity in the dominance of either model as $FF6_{OP}$ obtained lower GRS statistic (2.389) and $FF6_{OP}$ obtained higher $(\frac{As^2}{A|\alpha|^2})$ (0.128). For nsi quintile portfolios, the GRS rejected both $FF6_{OP}$ and $FF6_{CP}$ in explaining net stock issuance anomalous returns. The other metrics show that $FF6_{OP}$ wins over $FF6_{OP}$ as it performed better with a low GRS statistic of 3.854, low $A|\alpha|$ of 0.013, high $\frac{As^2}{A|\alpha|^2})$ of 0.260, and low $Sh^2(\alpha)$ of 0.112.

For *beme* quintile portfolios, the GRS rejected both $FF6_{OP}$ and $FF6_{CP}$ in explaining book-to-market equity anomalous returns. The $A|\alpha|$ is the same of both models. The other metrics indicate the supremacy of $FF6_{OP}$ as it performed well by scoring low GRS statistic (6.117) and a low $Sh^2(\alpha)$ (0.178). $FF6_{CP}$ performed well in $(\frac{As^2}{A|\alpha|^2})$ with a value of 0.46. For cf quintile portfolios, the GRS rejected both $FF6_{OP}$ and $FF6_{CP}$ in explaining cashflow-to-price anomalous returns. $A|\alpha|$ of both models is the same. Based on the values of other metrics, $FF6_{CP}$ seems to perform better with high $(\frac{As^2}{A|\alpha|^2})$(0.167) and low $Sh^2(\alpha)$ (0.118).Contrary to these metrics,$FF6_{OP}$ performed well in GRS statistics.

For ep quintile portfolios, the GRS rejected both $FF6_{OP}$ and $FF6_{CP}$ in explaining earningto-price anomalous returns. $A|\alpha|$ of both models is the same. $FF6_{CP}$ dominated $FF6_{OP}$by performing well in $\frac{As^2}{A|\alpha|^2}$ (0.073) and $Sh^2(\alpha)$ (0.104) whereas, $FF6_{OP}$ dominated $FF6_{CP}$ with a low value of GRS statistic. For gpp quintile portfolios, the GRS rejected both $FF6_{OP}$ and $FF6_{CP}$ in explaining gross profitability premium anomalous returns; however, the p val-

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ues are more than 10% level. $\frac{As^2}{A|\alpha|^2}$) $A|\alpha|$ of both models are the same. There is no clear winner as $FF6_{CP}$ performed better in $Sh^2(\alpha)$ and $FF6_{OP}$in GRS statistics.

For GPtoTA quintile portfolios, the GRS rejected both $FF6_{OP}$ and $FF6_{CP}$ in explaining gross profit-to-total assets anomalous returns. Both models obtained the same $A|\alpha|$. The other metrics prove the dominance of $FF6_{OP}$ with its better performance in GRS statistics (3.146) and ($\frac{As^2}{A|\alpha|^2}$) (0.218). However, $FF6_{CP}$ ruled in $Sh^2(\alpha)$. For otle quintile portfolios, the GRS rejected both $FF6_{OP}$ and $FF6_{CP}$ in explaining operating profit-to-lagged equity total assets anomalous returns. The p values are close to the 5% level.$A|\alpha|$ of both models is the same. However, $FF6_{CP}$ is superior to $FF6_{CP}$ with a high value of ($\frac{As^2}{A|\alpha|^2}$) (0.077) and a low value of $Sh^2(\alpha)$ (0.071). Meanwhile, $FF6_{OP}$ dominated $FF6_{CP}$ under the GRS statistic metric.

Based on the above results of one-way sorted anomalous portfolios, it can be said that the model $FF6_{OP}$ dominates $FF6_{CP}$ (with no significant exception) as it explains 5 out of 11 anomalous returns in the Pakistani stock market. Though, this explanation is not significant. Ali et al (2021) conducted a similar study on testing the performance of Fama and French models except for the $FF6_{CP}$ model. They tested nine anomalies, out of which three proved to be significant in the Pakistani market. There are two anomalies common in our studies. Similar to my findings, none of the models significantly explained the anomalies tested, but the five-factor model dominated other models in different metrics with no major exception.

6 Additional Test

I performed the factor redundancy test to check which factor/s is redundant in explaining the excess average returns in the Pakistani market. For this test, one factor was regressed against other five factors. Table 5 proved that the only factors that are not redundant in the Pakistani market are MKt, SMB_{OP}, and SMB_{CP} with positive intercepts of 0.015, 0.012, and 0.011 and more than two standard errors from zero per month. This finding supports the finding of Ali et al (2021) who also found *SMB* not being redundant in the Pakistani market. Furthermore, Fama and French (2015) and Chiah et al (2016) also proved the relevancy of *SMB* in the U.S. and outside the U.S.

All other factors are redundant in this market with insignificant intercepts and intercepts were not improved with the addition of *HML*, RMW_{OP}, RMW_{CP}, *CMA*, and *WML*in a model. The factors *HML*, *WML*, and *CMA* were also found redundant in the study of Ali et al. (2019) with tstat less than 1.96 though the rejection criteria in this study was of 1.65. The redundancy of *RMW* is contrary to the finding of Ali et al (2021) but consistent with the finding of Foye (2018) who found this factor redundant in Asia region. Besides this, my finding on

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Table 5: Models Performance in accommodating Anomalies

Model	GRS Statistic	P	$A\|\alpha\|$	$\frac{As^2}{A\alpha\|^2}$	$Sh^2(\alpha)$	$Sh^2(f)$
mc quintiles						
$FF6_{CP}$	5.942	0.000	0.027	0.177	0.162	0.302
$FF6_{OP}$	5.576	0.000	0.027	0.182	0.162	0.305
ol quintiles						
$FF6_{CP}$	4.395	0.001	0.016	0.108	0.12	0.302
$FF6_{OP}$	4.12	0.001	0.015	0.108	0.12	0.305
acc quintiles						
$FF6_{CP}$	3.079	0.011	0.011	0.287	0.084	0.302
$FF6_{OP}$	3.054	0.011	0.011	0.276	0.089	0.305
tacc quintiles						
$FF6_{CP}$	2.535	0.03	0.012	0.128	0.069	0.302
$FF6_{OP}$	2.389	0.039	0.012	0.113	0.069	0.305
nsi quintiles						
$FF6_{CP}$	4.274	0.001	0.014	0.236	0.117	0.302
$FF6_{OP}$	3.854	0.002	0.013	0.26	0.112	0.305
beme quintiles						
$FF6_{CP}$	6.585	0.000	0.021	0.046	0.18	0.302
$FF6_{OP}$	6.117	0.000	0.021	0.045	0.178	0.305
cf quintiles						
$FF6_{CP}$	4.338	0.001	0.015	0.167	0.118	0.302
$FF6_{OP}$	4.254	0.001	0.015	0.159	0.124	0.305
ep quintiles						
$FF6_{CP}$	3.818	0.003	0.017	0.073	0.104	0.302
$FF6_{OP}$	3.75	0.003	0.017	0.065	0.109	0.305
gpp quintiles						
$FF6_{CP}$	3.081	0.011	0.014	0.121	0.084	0.302
$FF6_{OP}$	2.962	0.013	0.014	0.121	0.086	0.305
GPtoTA quintiles						
$FF6_{CP}$	3.31	0.007	0.012	0.214	0.09	0.302
$FF6_{OP}$	3.146	0.009	0.012	0.218	0.091	0.305
otle quintiles						
$FF6_{CP}$	2.593	0.027	0.013	0.077	0.071	0.302
$FF6_{OP}$	2.575	0.028	0.013	0.076	0.075	0.305

Note: This table tests the performance of $FF6_{OP}$ and $FF6_{OP}$ model in explaining anomalies. The models are: Fama and French six-, and alternative six-factor model (2018). The considered significant anomalies are: firm size, operating leverage, accruals, net stock issuance, total accruals, book-to-market equity, earning-to-price, cashflow-to-price, operating profit-to-lagged equity, gross profit premium, and gross profit-to-lagged equity. This table explains how well the given models can explain the monthly excess returns on single-sorted mc portfolios, ol portfolios, acc portfolios, tacc portfolios, nsi portfolios, beme portfolios, cf portfolios, ep portfolios, gpp portfolios, GPtoTA portfolios, and otle portfolios. The table includes GRS-statistic and p-value of GRS test whether the model is rejected by this test in explaining an anomaly. A$|\alpha|$ is the average absolute alpha that which model produces lowest value of it. $\frac{As^2}{A|\alpha|^2}$ is the ratio of average variance of alpha to the average squared alpha. $Sh^2|\alpha|$ is the maximum squared Sharpe ratio of the alphas. $Sh^2(f)$ is the maximum squared Sharpe ratio of the factors of a given model. The sample period is from January 2000 to December 2017 (204 months).

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Table 6: Factor Redundancy Test

	Coefficient									R^2
	Int.	MK_t	SMB_{OP}	SMB_{CP}	HML	RMW_{OP}	RMW_{CP}	CMA	WML	
MK_t	0.015		-0.058		0.117	0.18		0.066	0.109	0.04
t-stat	*2.635*		*-0.699*		*1.514*	*1.962*		*0.764*	*1.108*	
SMB_{OP}	0.012	-0.043			0.093	-0.39		-0.153	0.148	0.23
t-stat	*2.377*	*-0.699*			*1.407*	*-5.238*		*-2.072*	*1.763*	
SMB_{CP}	0.011	-0.075			0.128		-0.338	-0.126	0.128	0.31
t-stat	*2.304*	*-1.3*			*2.188*		*-6.907*	*-1.851*	*1.601*	
HML	0.005	0.098	0.106			-0.584		-0.131	0.099	0.33
t-stat	*0.862*	*1.514*	*1.407*			*-7.892*		*-1.658*	*1.094*	
RMW_{OP}	-0.001	0.106	-0.312		-0.41			-0.34	0.176	0.48
t-stat	*-0.267*	*1.962*	*-5.238*		*-7.892*			*-5.471*	*2.36*	
RMW_{CP}	0.000	0.018		-0.574	-0.353			-0.279	0.104	0.38
t-stat	*-0.003*	*0.235*		*-6.907*	*-4.834*			*-3.211*	*0.998*	
CMA	-0.003	0.044	-0.139		-0.104	-0.386			-0.089	0.16
t-stat	*-0.601*	*0.764*	*-2.072*		*-1.658*	*-5.471*			*-1.099*	
WML	-0.002	0.057	0.104		0.061	0.155		-0.068		0.06
t-stat	*-0.395*	*1.108*	*1.763*		*1.094*	*2.36*		*-1.099*		

HML is in line with the finding of Mosoeu and Kodongo (2020) who found this factor to be redundant in South Africa. For *CMA*, other authors also proved its redundancy in China, South Korea, Singapore, Malaysia, and overall Asia (Lin 2017; Foye 2018; Mosoeu and Kodongo 2020).

7 Conclusion

There is limited research on the anomalous return patterns in emerging and frontier markets, though the importance of these markets is constantly increasing. To contribute to the literature of asset pricing in these markets, I carried out an out-of-sample study to test whether the Fama and French six- or alternative six-factor model explains the anomalous returns of Pakistani stocks. I took 11 anomalies in my sample. All these anomalies proved to be significant in the chosen market. The main findings show a strong size and value effect in Pakistan, less momentum, and no investment (measured using investment-to-asset ratio) and profitability (measured using cash and operating profitability) effect based on the factors results. However, the results of one-way sorted anomalies quintile portfolios showed profitability and investment effect with different proxies and sorting used. The findings show the effect of size. The economic justification is that investors prefer a premium for bearing an extra unit of risk and small firms carry a higher risk than big firms; therefore, they tend to have higher

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subsequent returns. Moreover, the leverage effect is also visible. Again, highly leveraged firms bear a high risk and have higher subsequent returns. The value effect is visible with other proxies, and it confirms that the value firms outperform growth firms with higher subsequent returns. Contrary to the findings of investment and profitability factors, I found an investment effect with accruals and net stock issuance. Also, the profitability effect is visible with gross profit measures and operating profit-to-lagged equity. It is known that firms having higher profits tend to have higher subsequent returns, and this phenomenon is obvious in profitability quintile portfolios. My findings suggest the investors, portfolio managers, and other practitioners on the long/short position they can take in their portfolios, considering the relationship between anomalies and subsequent returns. it is recommended to take long position in stocks having small size, low accruals, low net stock issuance, low cash flow-to-price, high operating leverage, high book-tomarket equity, high earnings-to-price, high gross profit premium, high gross profit-to-asset, and high operating profit-to-lagged equity and can short the vice-versa stocks. In short, all 11 anomalies have significant reasoning; therefore, I tested if the given models can explain these anomalies using a variety of time-series tests. These tests proved the dominance of the six-factor model in 5 out of 11 anomalies one-way sorted portfolios and the dominance of the alternative six-factor model in 4 anomalies with no clear winner in remaining anomalies. The six-factor model performed well in explaining more anomalies, so it is accepted as a dominant model. Nevertheless, this explanation is insignificant; thus, we require a better model to accommodate anomalies in the Pakistani stock market. This recommendation becomes more robust with the redundancy tests findings that value, profitability, investment, and momentum factors are redundant in the Pakistani market. Future research could explore other contemporary factor models and their empirical implications in the Pakistani stock market by incorporating time-series and cross-sectional tests.

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Appendix

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Table 7: List of Accounting Data Variables

This table includes a complete list of variables used for computing anomalies and factors. All the data is downloaded from Thomson Reuters.
Accounts payable (yearly item WC03040, hereafter abbreviated A/P)
Accrued payroll (yearly item WC03054, hereafter abbreviated AP)
Accrued taxes (yearly item WC03060, hereafter abbreviated AT)
Cash and short-term investment (yearly item WC02001, hereafter abbreviated C&SI)
Cost of goods sold (yearly item WC01051, hereafter abbreviated COGS)
Cumulative adjustment factor (yearly item AF)
Current assets (yearly item WC02201, hereafter abbreviated CA)
Current liabilities (yearly item WC03101, hereafter abbreviated CL)
Deferred income (yearly item WC03262, hereafter abbreviated DI)
Depreciation (yearly item WC04049, hereafter abbreviated Dep)
Depreciation and amortization (yearly item WC04049, hereafter abbreviated D&A)
Income taxes payable (yearly item WC03063, hereafter abbreviated ITP)
Interest expense (yearly item WC02999, hereafter abbreviated INT)
Net cashflow from operating activities (yearly item WC04860, hereafter abbreviated NCFO)
Net income before extraordinary items (yearly item WC01551, hereafter abbreviated NIBEI)
Other accrued expenses (yearly item WC03069, hereafter abbreviated OAE)
Outstanding shares (monthly and yearly item NOSH)
Prepaid expenses (yearly item WC02140, hereafter abbreviated PE)
Receivables-Net (yearly item WC02051, hereafter abbreviated REC)
Revenue (yearly item WC01001, hereafter abbreviated REV)
Selling, general, and administrative expenses (yearly item WC01101, hereafter abbreviated SG&AE)
Short-term debt and current portion of long-term (yearly item WC03051, hereafter abbreviated STD) Stock prices (item P)
Total asset (yearly item WC02999, hereafter abbreviated TA)
Total inventories (yearly item WC02101, hereafter abbreviated TI)
Total liabilities (yearly item WC03351, hereafter abbreviated TL)
Total return (item RI)

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Anomalies Calculations Firm Size mc It is computed as P times NOSH.
Operating Leverage ol It is computed as operating cost for the financial year ending t-1 divided by TA for the financial year ending t-1. Operating cost is computed as COGS plus SG&AE.
Book-to-market Equity beme It is computed as book equity for the financial year ending t-1 divided by market equity at the end of December t-1. Book equity is TA minus TL.
Cashflow-to-price - cf It is computed as cashflow for the financial year ending t-1 divided by market equity at the end of December t-1. Cashflow is NIBEI plus Dep.
Earnings-to-price ep It is computed as NIBEI for the financial year ending t-1 divided by market equity for the end of December t-1.
Gross Profitability Premium gpp It is computed as REV minus COGS scaled by lagged TA.
Gross Profit-to-assets GptoTA It is computed as REV minus COGS scaled by TA (here total asset is current, not lagged).
Operating Profits-to-lagged Equity otle It is computed as REV minus COGS (0 if missing) minus SG&AE (0 if missing) minus INT (0 if missing) divided by book equity. Book equity is TA minus TL. It is required to have a nonmissing value of at least one of the expenses.
Accruals acc It is computed as annual change in non-cash working capital minus D&A, divided by average TA for the previous two financial years. Non-cash working capital is computed as change in CA minus change in C&SI minus change in CL plus change in STD plus change in ITP.
Total Accruals tacc It is computed as NIBEI for the financial year ending t-1 minus NCFO for the financial year ending t-1, divided by average TA for the previous two financial years.
Net Stock Issuance nsi It is computed as as the annual log change in split-adjusted shares outstanding from t-2 to t-1. Split-adjusted shares equal NOSH times AF.

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