Idiosyncratic Risk Puzzle, Crash Sensitivity, and Cross-Sectional Return Predictability: Evidence from BRICS and Pakistan

Researcher
Saba Kausar
85-FMS/PHDFIN/F16

Supervisor
Dr. Syed Zulfiqar Ali Shah
Professor

Co-Supervisor
Dr. Abdul Rashid
Professor

Faculty of Management Sciences
International Islamic University Islamabad, Pakistan

TH-27190

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A thesis submitted in partial fulfillment of the requirements for the Degree of Master of Philosophy/Science in Management with specialization in Finance at
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In the name of Allah, the most merciful and beneficent

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Name of Student: Ms. Saba Kausar

Registration No: 85-FMS/PHDFIN/F16

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Viva Voce Committee

Prof. Dr. Hassan Raza
(External Examiner)

Prof. Dr. Khurram Shafi
(External Examiner)

Prof. Dr. Hameeda Akhtar
(Internal Examiner)

Prof. Dr. Syed Zulfiqar Ali Shah
(Supervisor)

Prof. Dr. Abdul Rashid
(Co-Supervisor)

Chairman Dept. of Business Administration

Dean, FMS 12/9/23.

FACULTY OF MANAGEMENT SCIENCES
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Dedication

I want to extend the word of thanks to the most caring person in my life, My Dearest Mother, who has always been the foundation of motivation and inspiration in my life, who has always been with me in thick and thin, black & white and rains or shines in every walk of my life. I want to thank my husband, son, and sisters, and brothers, particularly for their kind support throughout my study.

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Declaration

I solemnly declare that all the literature presented in the following dissertation is entirely based on research carried out to defend my thesis topic. This publication is a pioneer in its context and has neither similarity to any previously submitted thesis nor any copied material in its contents from any source except where due reference is mentioned. All of the published data are the result of my efforts, research, and analysis with the support of those mentioned in the acknowledgement, specifically my supervisors. Suppose, at some later stage, plagiarism is detected in the submitted research based literature. In that case, I will be fully responsible for all the consequences per the prevailing rules and laws of the approval committee.

Saba Kausar

PhD (Finance)

Faculty of Management Sciences

Appreciation And Gratitude

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Abstract

Despite the dominance of the CAPM models paradigm, investors have shown a longstanding interest in the question of whether idiosyncratic risk plays a role in determining expected returns. The impact of idiosyncratic risk on returns is well documented at the aggregate market level for developed economies in the literature. Still, not much is known about its impact at the individual stock level, specifically for developing and emerging economies. Further, the potential impact of crash sensitivities such as the idiosyncratic tail, and jump risk is ignored. In the existing literature, very less importance is given to the determinants of idiosyncratic risk and its pricing.

This study examined the impact of idiosyncratic risk, idiosyncratic tail risk, and jump risk on stock returns in Pakistan and BRICS member countries. It also explored the idiosyncratic risk, idiosyncratic tail risk, and jump risk puzzles by dividing firms into different groups based on their fundamentals, namely market risk, financial constraints, and liquidity position, to get an in-depth and better understanding of the underlying phenomena. Further, this study examined the determinants of idiosyncratic risk for the full sample as well as by dividing into groups: beta-based firms, liquid and illiquid firms, and financially constrained and unconstrained firms. Finally, we investigated whether the idiosyncratic risk is priced in the Pakistan and BRICS equity markets. For this, we construct a modified arbitrage score factor as a proxy for idiosyncratic risk. It is based on several new factors, such as an investor fear gauge, downside beta, downside co-skewness, and a sentiment index.

The analysis is carried out for the sample of all non-financial firms listed in the major stock markets of BRICS and the Pakistan Stock Exchange for the period of 20 years ranging from 2000 to 2019. Well-suited and sophisticated econometric techniques, namely quantile regression, random/fixed effects models, stochastic dominance, asset pricing models, and endogenous switching regression, are used to perform the empirical analysis. The results provide strong evidence of the idiosyncratic risk, idiosyncratic tail risk, and jump risk puzzles in all BRICS countries and the Pakistan Stock Exchange. Specifically, it is evident that the stock returns are significantly and negatively related to idiosyncratic risk, idiosyncratic tail risk, and jump risk during the examined period.

Consistent with the arbitrage asymmetry, the idiosyncratic risk puzzle for high-beta, illiquid, and financially constrained firms are stronger and statistically more significant than their counterpart firms. Further, a negative relationship between idiosyncratic tail risk and stock returns indicates the idiosyncratic tail risk puzzle in the case of the full sample and different groups of firms. Furthermore, the findings show the jump risk puzzle for all considered samples. Specifically, the jump risk puzzle is more pronounced for illiquid and financially constrained firms. However, no evidence for the jump risk puzzle is found in upper jump risk. Moreover, the results prove that the arbitrage score factor is a significant pricing factor in asset pricing.
The panel regression results show that firm size, market power, price-to-earnings ratio, return on equity, and dividend yield negatively relates to idiosyncratic risk. Yet, both leverage and liquidity are positively related to idiosyncratic risk. However, the sign of

momentum returns is mostly positive for the entire sample. The coefficient values for high-beta, financially constrained, and illiquid firms are more significant and larger than their counterparts for all sample countries. These results support the hypothesis of an under-diversified portfolio and suggest that the above-mentioned firm-specific variables are the significant determinants of the idiosyncratic risk.

Managers and investors in diverse investment portfolios may find this research very helpful, particularly for decisions related to portfolio diversification. The findings also suggest that the prospect theory can be used to forecast how investors will act to reduce disaster risks. The study's results also suggest that firm-specific characteristics correlated with idiosyncratic risk can help explain expected stock returns.

JEL classifications: G10; G11; G12; G14

Keywords: Firm-specific risk, Crash sensitivity, Determinants, Modified arbitrage factor, Asset pricing, BRICS, Pakistan

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List of Abbreviations

APT	Arbitrage pricing theory
AS	Modified mispricing arbitrage score factor
BE	Ratio of the book value of equity
BRICS	Brazil, Russia, India, China, and South Africa
CAPM	Capital asset pricing model
DY	Dividend yield
EBIT	Earnings before interest and taxes
EMH	Efficient market hypothesis
FC	Financially constraint
FSD	First order stochastic dominance
FUC	Financially unconstraint
IR	Idiosyncratic risk
ITR	Idiosyncratic tail risk
JR	Jump risk
LOA	Limit of arbitrage
ME	Ratio of market value of equity
MPT	Markowitz portfolio theory
OLS	Ordinary least square
PE	Price to earnings ratio
QR	Quintile Regression
SD	Stochastic dominance
SSD	Second order stochastic dominance
TSD	Third order stochastic dominance

Chapter 1
Introduction

1.1. Background of the Study

Market crash sensitivity leads to significant wealth destruction and severe contractions of consumption possibilities (Ganie, Wani, & Yadav, 2022). Consequently, stocks that exhibit disastrous results during market crashes due to extreme event risk (tail risk and jumps risk) are eventually unattractive assets for risk-averse investors (Barberis, Jin, & Wang, 2021). A recent strand of the literature also shows that investors dislike stocks with too many extreme event risks (Barunik & Nevrla, 2022). As a result, the value of investors' wealth deteriorates, and thus, they demand a high premium for investing in crash-sensitive stocks. (Chabi, Ruenzi, & Weigert, 2018).

Due to market crashes and disasters, firm-specific risks, namely, idiosyncratic risk (IR), idiosyncratic tail risk (ITR), and jump risk (JR), have received a lot of attention in capital markets, especially since the 2008 financial crises. These risks play a central role in stock markets. During a market crash, investors are at risk to make big losses with the stocks in their portfolios. Therefore crash-aversion prevails amongst investors, who want to hedge against these risks by holding crash-insensitive stocks. Accordingly, crash-sensitive stocks seem unattractive, as these stocks have bad returns during a market crash. Therefore, investors should pay more attention to these risks while creating their portfolios (Freire, 2021; Poudeh & Fu, 2022).

IR is defined as the risk attribute related to a specific asset and distinct from the uncertainty inherent in the market (Ang, Hodrick, Xing, & Zhang, 2009). According to Markowitz's portfolio theory (MPT) given by Markowitz (1952), IR does not need to be priced in asset markets as investors are expected to diversify their portfolios only to carry market risk. However, Ang, Hodrick, Xing, and Zhang (2006) and Fu (2009) have found the reverse to be true: IR should be priced in asset markets. Fu's research aligns with Merton's theory regarding the cost of information as a cause for a positive risk premium for IR. Merton (1987) shown that in the presence of market frictions where investors have limited access to information, investments in equity with high IR expect to be compensated for holding undiversified portfolios. Jones and Rhodes-Kropf (2003) also documented that investors demand a premium for holding stocks characterized by high, non-diversifiable risk. Behavioural studies such as Barberis, Huang, and Santos (2001) and Goyal and Santa-Clara (2003) offer a different type of asset pricing model based on the prospect theory, where investors value gains and losses differently, favouring perceived gains over perceived losses. Additionally, they find that stocks that have higher IR should earn higher expected returns.

ITR is the tail part of IR. It is an extreme event risk in asset markets (Long, Zhu, Chen, & Jiang, 2019). Unlike systemic risk, which is commonly taken into account in financial limitations (Qin & Zhou, 2019; Xu, Li, Jiang, & He, 2019), ITR primarily applies to the individual, asset class, and portfolio securities. It deserves more attention from crash-averse investors, as these investors are averse to financial disasters and are directly affected by extreme losses. Herliawan et al. (2020) showed that ITR had negative effects on stock return at the portfolio level. They showed the importance of extreme value to estimate ITR to explain the cross-section stock returns. Extreme value in IR, which is ITR, may stand out because investors may overweight the tail risk (Tversky & Kahneman, 1992), especially in the context of the leptokurtic distribution of stock return.

Large and significant discontinuous changes in stock prices are known as jumps (Jiang & Yao, 2013). JR is used to model extreme events, such as market crashes, which are essential components in asset price dynamics. Jumps are rare and not directly observable. Their properties are difficult to analyze. Previously, asset price dynamics and option pricing assumed that the jump intensity was constant (Merton, 1987). Further studies, for example, Pan (2002) and Eraker (2004), among others, assumed that the conditional jump intensity is an increasing function of the diffusive variance of asset returns. This is based on the idea that jumps tend to occur when the diffusive variance is high. They also documented that JR carries significant premiums depending on macroeconomic volatility. In particular, JR premiums are high when the growths of consumption and production in the economy are low and when the credit risk and volatility are high.

The nature of stock return volatility is central to portfolio theory, asset pricing models, and option valuation. Stock market volatility results from firm-specific (idiosyncratic risk) and market risks (systematic risk) (Noviayanti & Husodo, 2018; Shahzad, Fareed, Wang, & Shah, 2020). Systematic risk always remains, and portfolio diversification does not eradicate it. It is classified as an external risk because it is influenced by elements outside a company's control, such as economic conditions, sociopolitical conditions, and tax rules.

On the other hand, firm-specific risk can be eliminated because it is influenced by elements within a firm, such as market shares, management ranks, and annual earnings. It can be classified as an internal or diversifiable risk (Vongphachanh & Ibrahim, 2020). Firm-specific risk naturally changes over time as new information becomes available. However, it is mainly overlooked while making investment decisions. It is traditionally ignored because it generally can be diversified away. Nevertheless, due to the limits of arbitrage (LOA), it is actually impossible to diversify it completely (Ma, Whidbee, & Zhang, 2021).

The volatility of stocks refers to investment behaviour or temperament. Modern portfolio theory (Mortkowitz 1952), primarily relies on rationality and perfect market efficiency (Gbeda & Peprah, 2018). However, the LOA and bounded rationality become hurdles to market efficiency and the optimal decision-making process. The LOA theory proposed by Shleifer and Vishny (1997) asserts that rational traders use the restrictions placed during investment to arbitrate through price inefficiency. Thus, it is challenging for arbitrageurs to correct the mispricing of stocks with high IR. Then the returns on undervalued or overvalued stocks monotonically rise or fall with their IR. Therefore, IR is considered an arbitrage cost (Cao & Han, 2016; Stambaugh, Yu, & Yuan, 2015).

According to modern portfolio theory (Mortkowitz 1952), a higher risk is associated with higher returns and vice versa. As volatility increases in the financial market, investors demand a higher risk premium on risky securities for additional risk because investors are exposed to their risky securities. Theoretically, such a relationship is not possible without frictionless conditions such as perfect markets and well-diversified investors (Merton, 1987). The reward-risk trade-off rule is not as straightforward as the modern portfolio theory predicts. This rule does not hold in the real world for several reasons, mainly the LOA (Shleifer & Vishny, 1997). Because of the LOA, IR indifferently affects future returns on risky assets. For example, Levy (1998), Merton (1987), and Malkiel and Fama (1970) extended the standard capital asset pricing model (CAPM) by putting constraints on constructing portfolios and capturing the systemic and idiosyncratic risk of the security.

Further, LOA worsens the capital market mechanics, which weakens the role of stock price synchronicity in the reward-risk relationship (Rao & Zhou, 2019). Furthermore, IR captures information related to firm-specific risk. Thus, checking the behaviour of stock returns due to the change in their IR is very important.

Research on firm-specific risk in emerging and developing capital markets has become extremely important due to rapid economic development, economic liberalization, increased market capitalization, and foreign portfolio movements. Firm fundamental characteristics also play a significant role in affecting firm-specific risk. Although several options are available for investing in stock markets, the foremost challenge for investors is to select the stocks based on their fundamental characteristics (Kumari, Mahakud, & Hiremath, 2017). Therefore, finding the determinants of firm-specific risk is equally important.

Moreover, the determinants of firm-specific risk may differ across different types of firms. Therefore, to know what factors drive IR is very crucial. Besides, stock return volatility varies across firms' distinct characteristics, and the factors driving the volatility can contribute both positively and negatively to the economic growth of capital markets (Howell, 2020). So, it is likely that the firm-specific risk varies among different types of firms having distinct characteristics. The problem can be even more severe for firms with limited capital resources or financially constrained firms.

Moreover. the vulnerability to past stock returns must be higher for new, young, unseasoned stocks compared to the older and mature stocks with a high-performance reputation (Hurwitz, Chou, Chang, & Prakash, 2019). Therefore, examining the determinants of firm-specific risk based on various groups of firms is essential. Due to information uncertainty, arbitrageurs are uncertain about the true fundamental value of their arbitrage positions—the main empirical test concerns how the expected stock return relates to firm-specific risk. Under the costly arbitrage theory (Ross, 1976), this relation depends on whether the stocks are undervalued or overvalued. Suppose firm-specific risk prevents arbitrageurs from buying undervalued and short-selling overvalued stocks. In that case, the cross-sectional relation between expected stock return and firm-specific will depend on the direction of mispricing (Cao and Han 2016). Therefore, the measurement of stock mispricing is equally essential. For this, there is a dire need to construct an arbitrage score factor that price firm-specific risk.

1.2. Idiosyncratic Risk Puzzle

The pricing of IR has been one of the most popular topics for research for almost 50 years. Douglas (1968) and Lintner (1965) were the first who gave the importance of IR by explaining that the variance of residuals (calculated IR through residuals) has a significant relationship with stock returns. The recent studies by Poudeh and Fu (2022), Qadan and Shuval (2022) and Izcan and Bektas (2022) tried to reexamine this relationship using different techniques and methods. Some documented positive, and some explained negative or no relationship.

For instance, several studies found a positive and statistically significant relationship between IR and stock returns (Gu, Kang, & Xu, 2018; Liu, 2022; Rao & Zhou, 2019; Roy, Ahmad, Sadorsky, & Phani, 2022; Vo, Vo, & Nguyen, 2020). Merton (1987) argued that IR is relevant to asset pricing under more realistic situations where investors cannot invest in the market portfolio consisting of all the securities in the market as a matter of practicality. In addition to the difficulty of constructing the market portfolio, he further argued that tracking information on all securities is costly. Investors holding under-diversified portfolios will care about total risk (market risk and IR), not simply market risk. Therefore, firms with larger total variance require higher returns to compensate for imperfect diversification, suggesting that IR is positively related to the cross-section of expected returns if investors demand compensation for being unable to diversify away from firm-specific variance completely.

In contrast, Ang et al. (2006), Babenko, Boguth, and Tserlukevich (2016), Chabi et al. (2018), and Yao, Wang, Cui, and Fang (2019) found a significant negative relationship between IR and stock return. Recently, Qadan and Shuval (2022) and Alshammari and Goto (2022) also found a negative relationship between stock returns and IR. Ang et al. (2006) were the first who found a significant negative relationship between IR and stock returns and termed this relationship as a "puzzle." Their research results show low IR firms earning higher future returns than firms with higher IR. After these findings, this phenomenon got attention globally.

Several explanations for the IR puzzle appeared in prior studies. For instance, Bali, Cakici, and Whitelaw (2011) documented that maximum past returns capture lottery-like payoffs. However, the high IR stocks have higher positive skewness and more significant maximum past returns than low IR stocks. Chen and Petkova (2012) explained that IR could be a proxy for sensitivity to price volatility factors. Nevertheless, this explanation leads to the problem of switching in the sign of the IR puzzle. It implies that IR is correlated with the sensitivity to a systematic factor in the cross-section. This factor has a negative premium, and such a scenario is consistent with the negative IR puzzle among overpriced stocks and vice versa.

Shahrzadi and Foroghi (2022) also indicated the existence of the IR puzzle by explaining that the left tail risk plays an important role in explaining the IR puzzle. The reason for this is the falling stock price pressure with high left-tail risk on stocks with high IR. Another study by Kim, Lee, Lee, Ok, and Truong (2022) documented that underperformed firms having high IR leads to the IR puzzle.

Finally, there is also another group of studies that does not find any significant association between IR and stock returns (see, for example, Kim et al. (2022), Kong, Pan, Sun, and Taghizadeh-Hesary (2020), Liu, Kong, Gu, and Guo (2019), and Zaremba, Czapkiewicz, and Będowska-Sojka (2018). These studies have suggested that the IR puzzle is an apparent phenomenon because of estimating the IR through different methods.

1.3. Crash Senstivity and Tail Risk

Tail risk is defined as extreme event risk in asset markets. Many researchers and quantitative strategists, for instance, Cirillo and Taleb (2020), Gao, Lu, and Song (2019), and Aboura and Chevallier (2018), have argued for the importance of paying more attention to the tails distribution of returns. Traditional risk management methods undervalue the severity and frequency of stock market tail events. Prudent asset managers tend to be cautious about the risk of losses that may cause damage or ruin portfolios (Bhansali, Gingrich, & Longstaff, 2008). The financial crisis due to IR is explained by ITR (Herliawan, Kim, Saputra, & Ferdinand, 2020). After the financial crisis of 2007-08, ITR is considered an important firm-specific risk. In particular, portfolios with high IR exhibit negative and statistically significant tail risk betas (Aboura & Arisoy, 2019). Freire (2021) also documented that tail risk is at its peak in stock market crashes, political shocks, or disaster events such as the coronavirus pandemic.

Black Swan theory, postulated by Taleb (2007), refers only to unexpected events of large magnitude and consequence and their dominant role in history. Such events, considered extreme outliers, collectively play vastly more significant roles than regular occurrences. It includes an event likely to occur at both ends of a standard distribution curve. Tail events and non-normal distributions are widespread in finance. Extreme value theory (Fisher & Tippett, 1928) is based on the study of tail risk. The extreme value theory states how we model extreme events and their associated risks using the generalized extreme value method (Cirillo & Taleb, 2020; Long, Jiang, & Zhu, 2018).

TR is an event with a small probability of happening. Professor Bob Conroy said in 2015 that "In every event, there are tails; there are really, really good things that can happen and really, really bad things." Tail risk is such type of risk which occurs when the probability of investment moves more than three standard deviations from the average. As returns are asymmetrically distributed, and investors are averse to disasters, tail risk is significant in asset pricing (Campbell, Lettau, Malkiel, & Xu, 2001). Menezes et al. (1980) indicated that, although with low probability, investors tend to avoid positions that might cause huge losses. Aboura and Arisoy (2019) reported that unusual disasters or tail risks are significant in explaining the IR puzzle in asset pricing.

MPT (Markowitz, 1952) has been the crux of the asset allocation paradigm, which assumes that asset returns follow a normal distribution with constant volatility (Hocquard, Ng, & Papageorgiou, 2013). The expected shortfall in stock returns contains two elements: volatility (conditional variance) and the shortfall in returns filtered by volatility (or standardized). Thus, tail risk is the additional risk of having fat-tailed return distributions. Further, due to the time-varying nature of volatility, asset returns are expected and often behave non-normal, which increases the likelihood of adverse portfolio tail events (Andersen, Fusari, & Todorov, 2019). Nonetheless, long periods of financial distress, such as the dot-com bubble (2000), the Lehman default (2008), and the European debt crisis (2009), encourage scholars to focus more on disaster, crisis, and tail risk.

1.4. Stock Price Jumps and Jump Risk

Event risk can also be associated with a changing portfolio value due to large swings in market prices. It is also referred to as "gap risk" or "jump risk." These are extreme portfolio risks due to substantial changes in overall market prices due to news events or headlines that occur when regular market hours are closed. Further, significant discontinuous changes in stock prices are known as jumps and proxy for substantial stock market information shocks (Jiang & Yao, 2013). A jump in cross-sectional return is very important as high jump volatility betas have a negative relationship with high jumps and bond returns. (Chen, Wang, & Wu, 2022). There is ample empirical evidence for the existence of jumps or discontinuities in the price of the market portfolio (Leong & Kwok, 2022; Odusami, 2021), suggesting that the risk associated with market price jumps differs from the risk associated with "smooth," or continuous, price moves.

Jumps also feature prominently in many equilibrium-based models seeking to rationalize the collective behaviour of stock and option markets. The existing empirical analyses and theoretical models are not enduring. The apparent "high" price of market JR is widely regarded as puzzling. Several research studies suggested that volatility and JR may be similar (Bakshi and Kapadia (2003). However, the market tends to be more volatile at the time of extreme returns. This phenomenon separating the jump and volatility risk became an empirical challenge (Zhang, Zhou, Chen, & Liu, 2022). However, Cremers, Halling, and Weinbaum (2015) documented that both volatility and JR are pretty different. They can be measured separately by using option returns, and economically both have importance. They also documented that although both volatility and JR factors impact the stock returns. However, the JR has a more significant impact than volatility does. Ebrahimi and Pirrong (2020) also gave importance to the upside JR and documented that upside JR has a significant impact on stock returns

A jump is a source that attributes to a return fat tail distribution. Investors cannot form a market portfolio to diversify the firm-specific risk in a less efficient market. In such cases, firm-specific and industry-level risks may influence return premiums and affect asset prices. Thus, the standard capital asset pricing model (CAPM) cannot explain the returns as perfectly as the theory says. General equilibrium models can be used to shed light on economic mechanisms that drive, jump and risk premia volatility ((Jiang & Yao, 2013).

1.5. Overview of BRICS Countries

BRICS acronyms for Brazil, Russia, India, China, and South Africa. These countries have experienced remarkable growth for the last 20 years, playing an ever more significant role in the global economy. BRICS contribute 20.2% to global GDP and 41.3% to the world population. BRICS countries are significant beneficiaries of global investment flows, attracting 20% of world foreign direct investment inflows and accounting for around 24.6% of total equity market capitalization. This is the core reason of sample selection.

Further, The BRICS countries have benefited from a considerable increase in foreign investment inflows over the past two decades as investors have sought out higher-yielding investments and reduced their exposure to risk. As a result, net portfolio inflows have peaked. In the end, the ongoing strengthening of bilateral and intergroup trade cooperation has led to interdependence across key macroeconomic variables such, portfolio investments, gross domestic product, external account balances, , interest rate spreads, foreign direct investment, foreign liquidity reserves and sovereign credit risk (Belli, 2021).

The considered sample is distinguished from other emerging economies due to their economic and demographic potential and has become the most influential and significant economies in the 21st century. According to a recent estimate of the world's largest economies, four of the five BRICS countries will be in the top ten by 2050 as these members have experienced high growth for large parts of the last decade, and each nation is different in its unique way. Moreover, among the BRICS countries, India has the fastest-growing GDP, followed by China, Brazil, Russia, and South Africa. These countries have high growth rates, making their cooperation a potent force in today's global economy (Belli, 2021). Following are the details about the major stock exchanges of BRICS member countries.

1.5.1. São Paulo Stock Exchange

The main stock exchange in Brazil is the So Paulo Stock Exchange (SPE), established in 1890. It is one of the biggest companies in Brazil in terms of market value and has a substantial global presence in the stock market industry. The SPE and Brazil, Mercantile and Futures Exchange merged in 2008, forming the BM&F Bovespa Exchange. Nowadays, it is referred to as B3 or Brazil, Bolsa, Balco. The CME Group and the exchange are strategic partners (American global markets company). There are 351 companies overall listed on the exchange, and just four are foreign corporations. By February 2021, the exchange's share trading for stocks had a value of $129 billion.

The index has served as a benchmark for investors of Brazilian stocks worldwide since it was established in 1968. The IBOVESPA's performance has improved over the past five years, going from 65,403 BRL on April 1, 2017, to 121,570 BRL on April 1, 2022. On April 19, 2021, 82 firms were a part of the index. The IBOVESPA is reconstituted every three months and is weighted on a free float. In the capital markets, it represents around 80% of trades and financial volume.

1.5.2. Moscow Stock Exchange

The Moscow Interbank Currency Exchange and the Russian Trading System, the two biggest exchanges in Moscow, were combined to become the Moscow Stock Exchange

(MOEX) on December 19, 2011. The largest exchange in Russia, MOEX, makes it possible to trade stocks, bonds, derivatives, foreign exchange, money markets, and precious metals. The MOEX Index is a stock index that measures the performance of the top 50 most liquid and significant Russian stocks from ten different industries. Because it is a capitalization-weighted composite index, the value of the index will be dominated by companies with higher market capitalizations.

On February 15, 2013, MOEX became public following an IPO and contributed to the $400 million or 15 million rubles in funding. Shares of MOEX trade under the ticker name MOEX. About 63% of shares were in the free float as of December 2021, while the Central Bank of Russia (11.75%), Sberbank (9.9%), Vnesheconombank (8.4%), European Bank for Reconstruction and Development (6.1%), and US asset management company Capital Research and Management Company, which oversees more than $1.3 trillion in retirement assets globally, each held blocks of shares.

1.5.3. National Stock Exchange

India's biggest financial market is the National Stock Exchange (NSE). Since its incorporation in 1992, the NSE has grown into a sophisticated electronic market with the fourth-highest volume of global equity trading. With the introduction of the wholesale debt market, trading started in 1994. The NSE was one of the biggest stock exchanges in the world as of June 2020, with a total market value of $2.27 trillion.

The flagship index, the NIFTY 50, represents most of the total market capitalization on the exchange. The total traded value of stocks listed on the index made up almost half of all stocks on the NSE in 2020. The index itself covers 12 sectors of the Indian economy across 50 stocks. Besides the NIFTY 50 Index, the NSE maintains market indices that track various market capitalizations, volatility, specific sectors, and factor strategies.

1.5.4. Shanghai Stock Exchange

China's biggest stock exchange is the Shanghai Stock Exchange (SSE). The China Securities Regulatory Commission is in charge of this nonprofit corporation. On the SSE market, stocks, money, bonds, and derivatives are all exchanged. Every listed firm has two primary classes of equities traded on the exchange: A-shares and B-shares. B-shares are often available for overseas investment and have U.S. dollar quotes.

A-shares are solely accessible to overseas investors and are quoted in yuan. Once state-run firms such large commercial banks and insurance companies make up the majority of the SSE's overall market capitalization. The exchange has only been home to several of these firms since 2001. In terms of overall market capitalization for equities exchanges, the SSE comes in fourth place globally, trailing only the NYSE, Nasdaq, and Tokyo Stock Exchange.

1.5.5. Johnsburg Stock Exchange

The largest stock exchange in Africa is the Johnsburg Stock Exchange (JSE). The JSE was created in 1887, during the first South African gold rush. When the Global Federation of Exchanges was established in 1963 and the first piece of law regulating financial markets was passed in 1947, the JSE switched to an electronic trading system in the early 1990s. The bourse was demutualized in 2005 and listed on its exchange. The

South African Futures Exchange and the Bond Exchange of South Africa were later acquired by the JSE in 2001 and 2009, respectively. The bond market was transferred from the JSE to the Bond Exchange of South Africa in May 1996, and the latter was granted a license under the Financial Markets Act to operate as a financial market. In 2000, it relocated from downtown Johannesburg to Sandton, where it is now located in Johannesburg, South Africa. As of March 2022, the JSE had 473 listed companies and a market value of US$1.36 trillion.

The performance of listed firms in South Africa is frequently monitored by the JSE All-Share Index, which is commonly regarded as the benchmark index. The JSE All-Share Index, according to the index provider, accounts for 99% of the total market capitalization of all ordinary securities listed on the JSE's main board. Another well-liked method for monitoring the performance of large and mid-cap JSE equities is the MSCI South Africa Index. After free float adjustment, the index includes 85% of South Africa's market capitalization. The JSE Top 40 Index is a blue-chip index that measures the performance of the top 40 listed South African firms by market capitalization.

1.6. Overview of the Pakistan Stock Exchange

The largest stock market in Pakistan, Pakistan Stock Exchange (PSX), formerly Karachi Stock Exchange (KSE), was founded on September 18, 1947, with the arrival of the educated and affluent Muhajirs. Karachi Stock Exchange Limited was formed on March 10, 1949. The KSE launched as KSE 50 with five companies and a market valuation of Rs. 37 million ($160,000). The KSE has facilitated capital formation for over 60 years, benefiting a wide range of participants, including individual and institutional investors.

By the late 1980s, another index had been introduced due to an increase the number of listed companies and trading activities. The launch of the KSE-100 Index happened on November 1st, 1991. A futures index was needed by 1995, and on September 18, 1995, the KSE All Shares Index was introduced. Two other indexes—the KSE-30 Index and KMI-30 Index—were developed in the late 1990s to meet the needs of the investor community. Beginning in the late 1990s, work was done on a fully automated trading system. The Karachi Automated Trading System, or KATS, could handle more than 1 million daily deals and was introduced in 2002. The KSE named it the "Best Performing Stock Market of the World" in the same year.

Under the Stock Exchanges (Corporatization, Demutualization and Integration) Act 2012, the Karachi Stock Exchange, Lahore Stock Exchange, and Islamabad Stock Exchange were integrated in 2016 to establish the Pakistan Stock Exchange. As of January 30th, 2019, there were 559 listed firms in 35 categories throughout the PSX as of January 11, 2016, with a total market capitalization of US $91 billion. From 2009 2016 to 2016, it was regarded as the fifth best-performing market worldwide. It consists of domestic and international firms with stated capital above US $10 billion. The PSX-100 index, with a base point of 1000, has replaced the KSE-100 index. Between 2009 and 2016, PSX remained one of the top stock exchanges in the world, and in 2016 it was regarded as the fifth greatest market in the world.

The Financial Times Stock Exchange categorizes PSX as a Secondary Emerging Market. In May 2017, Morgan Stanley Capital International (MSCI) Emerging Market replaced PSX as the classification. The economy expanded from 2013 to 2018, and the stock market saw improvement. This is mostly attributable to substantial Chinese investment in the shape of the China-Pakistan Economic Corridor. A Chinese group purchased 40% of PSX's strategic shares in December 2016 for $85 million. However, it turned into the stock market with the worst performance after falling 28% from its peak in May 2017 to December 2017. After recovering from its position in December 2017, the stock market had conflicting patterns in 2018. 548 companies are listed on PSX as of September 13th, 2019, with a market capitalization of $6,928.045 billion (Shafique, Ayub, & Zakaria, 2019).

1.7. Problem Statement

Fundamental relation between risk and expected return is that an increased exposure to risk ought to pay off in an increased expected return, ceteris paribus. Thus, the results found by Ang et al. (2006) are highly unexpected. On the other hand, the reverse should also not be true if MPT hold. The return differential should be non-existing or at least non-significant as investors are expected to diversify their portfolios in such a way that only market risk is left. Among various arbitrage costs, IR is the most prominent holding cost (Pontiff, 2006; Shleifer & Vishny, 1997), which is mainly overlooked. Further, the LOA lead to market inefficiency that doubts the validity of capital asset pricing models. Market inefficiency leads to mispricing. If the arbitrage cost is high, there would be more significant mispricing due to the costly arbitrage process. More recent models, such as Roll (1977) Ross' Arbitrage Pricing Theory, APT, cannot explain the peculiar finding that stocks with low IR earn higher returns than stocks with high IR earn low returns. He highlighted the ambiguity in the subject between the different empirical findings regarding IR and return and the ambiguity between asset pricing theories.

Market anomalies or puzzles are the core problem in an efficient capital market. Ang et al. (2006) were the first who found a significant negative relationship between firm-specific risk and stock returns and termed this relationship as a "puzzle." Their research results show low IR firms earning high future returns than firms with higher IR. After that, this dilemma got attention globally, in contrast to the modern portfolio theory, which states that the high-risk exposed firms should have greater returns. In addition, the performance of the stock in terms of returns got worsened when the level of IR increased. This phenomenon too is also against the reward-risk trade-off rule (Morkowitz 1952). Further, the extreme events risks such as jump risk and tail risk may seriously disturb the current and long-term performance of firms. Merton (1987) and Malkiel and Xu (2002) argued that poorly diversified portfolios require an extra risk premium for holding stocks with high IR. In actuality, those firms which have high tail and jump risk have low returns resulting in anomalies in capital markets. Hence, one of the critical questions arises as how different types of firm-specific risks such as IR, ITR, and JR affect the expected cross-sectional returns on stocks in less efficient capital markets remains an open debate.

The CAPM suggests that IR does not matter in pricing risky assets given that IR is assumed to be diversified away since investors hold a proportion of the well-diversified market portfolio. In fact, IR plays a role in explaining returns of risky assets due to LOA and investors do not always hold well-diversified portfolios. So rather than a debate about the impact of IR on stock returns in the diversification framework, the researcher should focus the question on what factors arise the firm-specific risk. As IR is firm-specific risk and stock fundamental are proxies for firm-specific information, hence what are the core drivers to determine IR is still an open debate under an imperfect capital market.

Market inefficiency leads to mispricing. If the arbitrage cost is high, there would be more mispricing due to the costly arbitrage process and this market inefficiency cast doubts on the validity of capital asset pricing models. The IR is the most prominent holding cost that prevents investors to hold diversified portfolios. Due to these arguments, the asset pricing models in standard finance are misspecified. Therefore, IR is a missing risk factor for the asset pricing models.

1.8. Research Gaps

Research about the volatility of stock markets, especially in emerging and developing markets, has significant importance due to political liberalization, rapid economic growth, rising stock market liquidity, and portfolio flows. In recent years, there is also an extensive debate about IR and expected returns. Limited research studies have examined the relationship between IR and cross-sectional stock returns which is only for developed countries. Further, the empirical studies show the puzzling relationship between IR and stock returns (Brandt, Brav, Graham, & Kumar, 2009; Chabi et al., 2018; Long et al., 2018; Stambaugh, Yu, & Yuan, 2015). Furthermore, firm-specific risks like tail and JRs have become part of recent research issues in developed countries (Chabi et al., 2018; Chow, Li, & Sopranzetti, 2018; Long et al., 2018) and the literature is also silent about the behaviour of IR corresponding to market crash sensitivities, market dynamics, and investors' sentiments that might cause these puzzles.

The current study identifies several gaps in the existing literature that should be bridged to obtain a complete, clear, and comprehensive understanding of the relationship between

IR, jump tail and tail risk, and expected cross-sectional return. By reviewing the empirical literature, the current study specifically has identified the following research gaps at the international level and related to emerging and developing stock markets.

The first gap is related to reconfirming the puzzling relationship between IR and stock returns through different approaches and parametric and non-parametric techniques. There is a massive controversy about the relationship between IR and expected stock returns. For instance, the research studies on developed and advanced equity markets (Fu (2009); Gu et al. (2018); Rao and Zhou (2019); Spiegel and Wang (2006); Xu and Malkiel (2003)), among others, have found that stocks have high IR have higher expected returns. Along similar lines, there are several other studies have found that there is a negative association between IR and expected returns for highly developed and advanced capital markets (see, for example, Ang et al. (2006); Chabi et al. (2018); Evgeniou, de Fortuny, Nassuphis, and Vermaelen (2018); Yao et al. (2019)). However, while consisting of the classical asset pricing model, some studies have documented that there is no significant relationship exists between IR and cross-sectional returns (see, for example, Bali, Cakici, & Levy, 2008; Hemler & Longstaff, 1991; Nartea, Wu, & Liu, 2013; Zaremba et al., 2018). We examine the IR puzzle in developing and emerging stock markets based on the abovementioned studies. Further, in the existing literature, no study has been found that examines the IR puzzle for different groups of firms. Although there is a discussion available about the IR puzzle, for instance, those firms with high IR have low returns. However, there is also a dire need to investigate whether (and how) the relation between IR and returns varies groups based on fundamentals such as market risk, financially constraints, and liquidity position to get an in-depth and better understanding of the underlying phenomenon.

The second gap is related to the determinants of IR. What factors could explain IR remain unclear in the literature. When considering developing and emerging countries, we only found two studies. One empirical study was for India, and the other was for the Indonesian market. Specifically, Kumari et al. (2017) investigated the determinants of IR in India. They found that firm size, momentum, book-to-market value, liquidity, EBIT, and the cashflow-to-price ratio are the significant determinants of IR. The main drawback of their study is that they used the GARCH model to calculate IR that follows the normal distribution assumption for the stock returns. The other study has tried to explore the determinants of IR based on the nature of ownership instead of using the fundamental level of variables for Indonesia (Monica & Ng, 2018). According to their findings, foreign ownership, management, and public ownership negatively affect firm-specific risks. However, their research did not consider a firm's fundamental factors influencing IR. Most of the literature is unclear on what precisely determines IR in emerging countries. Secondly, no study explores the drivers of IR. Therefore, there is a dire need to find the empirical determinants of IR, especially in top emerging stock markets, because of their diverse and unique features compared to developed and developing stock markets. Thirdly, no comprehensive study is available on the determinants of IR based on different types of firms (divided based on the firm's fundamental characteristics).

By doing this, we can answer whether the determinants of IR vary based on different types of firms. For instance, to find whether the sensitivity of firm-specific risk is different in financially constrained and unconstrained firms, low-, high-, and medium-beta firms, and liquid and illiquid firms. The rationale behind this objective is that there is a possibility that the sensitivity of firm-specific risk towards financially constrained firms, high-beta firms, and illiquid-firms are higher than their counterparts. Fourthly, we employ portfolio analysis to uncover some fascinating facts about stock fundamentals as various stock fundamentals are linked to IR and uncover a few intriguing discoveries about the most prevalent and well-documented anomalies in the modern finance literature, such as the size effect, P/E ratio (price-to-earnings), and dividend anomaly.

The third gap is related to the extreme event risks named ITR and JR. The role of ITR and JR in affecting stock returns attracted much less attention. Existing studies have documented the relationship between tail risk and JR with stock returns but only done on the downside risk (e.g., lower tail risk and negative JR) (Arouri, M'saddek, & Pukthuanthong, 2019; Gao et al., 2019). Hence, the relationship between upper tail risk and positive jump risk with stock returns is ignored. Therefore, we examine the relationship between ITR (both upper and lower tail risk) and JR (negative and positive JR) with stock returns to fill the existing gap. Further, to our knowledge, no study is available to check the ITR and JR puzzle in firms' distinct groups. Therefore, to check the strength or intensity of the tail and JR puzzle for different firms, the current study investigates the relationship between tail risk and JR stocks with stock returns based on the firms' distinct groups, such as financially constrained and unconstrained firms, low-, high-, and medium-beta firms, and liquid and illiquid firms.

The fourth gap is related to the pricing of IR. The existing literature examined the relationship between IR and cross-sectional returns based on the consideration of stock mispricing (Cao & Han, 2016; Evgeniou et al., 2018). However, no study is available on the pricing of IR in the asset market. Therefore, there is a need to construct a factor into asset pricing models that should price the IR. Hence, the current study constructed a modified mispricing factor. The factor includes several new behavioural factors such as investor fear gauge, downside beta, downside co-skewness, and a sentiment index.

1.9. Objectives of the Research

Firm-specific and extreme event risks in asset markets are important considerations for investors when making investment decisions. The core objective of this study is to examine IR, JR, and ITR puzzles. Further, the determinants and pricing of IR are also included in the core objectives. Furthermore, this study examined the puzzles in different groups of firms. Specifically, the present study focuses on achieving the following objectives:

1. To examine the idiosyncratic risk puzzle.
2. To examine whether the relationship between idiosyncratic risk and returns differs for a different group of firms (beta-based firms, liquid and illiquid firms, and financially constrained and unconstrained firms).
3. To examine the empirical determinants of idiosyncratic risk in overall firms and in different groups of firms
4. To propose a modified arbitrage score factor as a proxy for pricing idiosyncratic risk in capital asset pricing models.
5. To examine whether the idiosyncratic risk is really priced in the equity markets by adding the modified arbitrage score factor in asset pricing models.

6. To explore the relationship between idiosyncratic tail risk (lower and upper tail) and cross-section stock returns.
7. To explore the relationship between jump risk (positive and negative jumps) and cross-section stock returns.
8. To investigate the idiosyncratic tail and jump risk puzzle by dividing firms into different groups.

1.10. Research Questions

In this study, the following research questions are investigated.

1. Does the idiosyncratic risk puzzle exist?
2. Does the relationship between idiosyncratic risk and returns differ for a different group of firms (beta-based firms, liquid and illiquid firms, and financially constrained and unconstrained firms)?
3. What are the empirical determinants of idiosyncratic risk in overall firms and in different groups of firms?
4. Does the modified arbitrage score factor price idiosyncratic risk in asset pricing models?
5. Does the idiosyncratic tail risk puzzle exist?
6. Does the idiosyncratic jump risk puzzle exist?
7. Do the idiosyncratic tail and jump puzzles exist in different groups of firms?

1.11. Significance and Contribution of the Study

1.11.1. General Significance

The present study contributes to the domain of firm-specific risks, namely, IR, ITR risk, and JR. By exploring these puzzles that might affect investment decisions, investment performance, and market efficiency. ITR and JR are the new concepts along with IR compared to other financial risks. In emerging and developing stock markets, it is very important to check the relationship of stock returns with IR, ITR, and JR, which could lead to inefficient markets and cause market anomalies and puzzles.

Nevertheless, the literature on emerging and developing financial markets related to this context is minimal. Examining these puzzles has curious implications for a better understanding of market dynamics and volatility in financial markets. This research examines IR, ITR, and JR and understanding such puzzles and stock market abnormalities allows appropriate corrective actions. Further, it is essential to offer conceptual contributions for IR, ITR, and JR puzzles. Therefore, to fully understand the underlying relationship, this study contributes to reconciling the ambiguous and contradictory findings of previous research studies on firm-specific risks and stock returns.

1.11.2. Specific Significance

1.11.2.1. Theoretical Contributions

This study significantly contributes to IR, ITR, and JR puzzles literature. Emerging and developing stock markets are likely to suffer high volatility and asymmetric information (Dao, 2014). The study related to IR, ITR, and JR about emerging economies can provide more profound evidence of the said risks in cross-sectional stock returns in a single time frame. Thus, the study provides the following theoretical contributions to the existing literature.

Firstly, IR, ITR, and JR are essential components of total volatility. It is important to evaluate the security, options, and other derivatives because of the asset pricing and other financial applications, as volatility is used as a parameter. Since volatility is not constant, examining the time-varying firm-specific risks is necessary. Further, examining the determinants of IR by considering firms' fundamentals may help to develop better asset pricing models. Secondly, Bartram, Brown, and Stulz (2009) documented that emerging markets are more prone to "bad" volatility than developed ones. Motivated by the studies mentioned in the gap section, this study examines the role of extreme risks on both sides (upper and lower ITR and positive and negative JR) in the cross-sectional stock returns would be a significant contribution. Thirdly, according to the costly arbitrage theory, the equilibrium relation between IR and cross-sectional returns should vary with the magnitude and direction of mispricing. Therefore, this is the first study that constructed a modified arbitrage score factor and added it to the Fama and French five-factor CAPM model and checked whether IR is really priced in the equity markets of emerging and developing countries.

1.11.2.2. Practical Contribution

With the gradual change in investment patterns, investors' expectations vary extensively. They try to make beneficial strategies. In other words, investor behaviour is extremely important to understand why it ensures investment choices and how it reacts in a state of uncertainty (Sapra & Zak, 2010). The research has intrusive implications for our perception of financial market conditions. In an unstable economy, it is proposed that there may be incentives for arbitration; due to time-varying uncertainty, creditors can seek to benefit by controlling all forms of risk (for instance, IR, ITR, and JR). This research helps local and foreign investors with portfolio management by analyzing IR, ITR, and JR.

The research study on IR, ITR, and JR is motivated by several practical contributions. First, according to the findings of Goetzmann and Kumar (2004), more than 25% of retail investors keep only one stock in their portfolio, more than half of investor portfolios carry no more than three stocks, and less than 10% of investor portfolios hold no more than ten stocks. Therefore, investors have been exposed to high firm-specific risks. A better understanding of the risks is valuable to investors since recent research has shown that investors tend to hold under-diversified portfolios and that the said risks should be priced.

Secondly, creditors are the key stakeholders of the firms, particularly those with high levels of idiosyncratic and extreme event risks. The current study helps creditors while devising contracts with those firms. In light of the arguments of Acharya, Amihud, and Litov (2011), when credit is a more significant funding source, creditors influence firm decisions and limit the firm from taking different risks.

Thirdly, regulatory authorities are responsible for maintaining capital market efficiency, so this study assists those bodies. For example, evidence of the existence of IR, ITR, and JR puzzles helps the government implement its policies and security regulations. They prohibit the trading of insiders and have access to private information. After detecting these puzzles, the regulatory authority must educate the firm managers. This study would also be significant for portfolio construction and risk management investors.

1.11.3. Contextual Contributions

The research studies of IR, ITR, and JR and their sensitivity towards market dynamics are mostly done on advanced, well-established, and regulated stock markets. However, this research is on developing and emerging economies with less efficient capital markets with weak corporate governance and investor protection systems. So, this research greatly emphasizes adding empirical work related to IR, ITR, and JR. Following are the significant contextual contributions.

First, rather than measuring IR, ITR, and JR at the aggregate level, the current study calculated these risks at firm levels and examined how these risks affect the cross-section of stock returns. Specifically, this study applied parametric and non-parametric approaches to explore the relationship between firm-specific risks and their returns. The second contextual contribution is that we analyzed IR, ITR, and JR puzzles using the quintiles regression approach. The third contextual contribution is about the said puzzles in different groups of firms. By doing this, firms are divided into different categories based on their fundamentals such as market risk, financially constraints, and liquidity position.

1.12. Structure of the Study

The remainder of the thesis is structured as follows. Chapter 2 is a review of the literature. The chapter mainly explains the theoretical framework and literature related to

IR, ITR, and JR. It first describes the main and supporting theories and then presents existing literature on the relationship of IR, TR, and JR with stock returns. It also documents the literature that made efforts to solve the IR puzzle. The study also discusses the important role of IR in the stock market with different methodologies.

Chapter 3 is Data and Methodology. The chapter starts with the study's philosophical stance, the details about the data, sample size, data sources, and sampling procedure for selecting data. The next research design explains the study and focuses on the proposed research methodologies and different statistical tools used. Afterwards, we thoroughly explain the parametric and non-parametric approaches to examine the IR puzzle. Next, the details about the methodologies used to examine the ITR and JR puzzle are documented. Then, we give a detailed explanation of the construction of arbitrage mispricing factors for IR pricing. In addition, the chapter also includes details about the portfolios and different variable construction. Moreover, a detailed procedure for how firms identify and divide into different groups is also discussed.

Chapter 4, Results and Discussion, explains the results of the IR puzzle and documents the existence of IR by providing the results through parametric and non-parametric methods. Next, the results of the IR puzzle in different groups are presented. After that, ITR and JR risk puzzles in overall and different groups of firms are presented. Then, the results of determinants and pricing of IR are shown. Finally, we presented the IR and ITR trends in all sampled countries through graphical analysis.

Chapter 5 presents the concluding comments on the major findings, followed by the study's policy implications, limitations, and future directions. In major findings, we discuss and answer the research questions. After that, based on the findings, the importance of IR, ITR, and JR in emerging and developing countries is discussed. The policy implications section gives important suggestions to investors, creditors, the government, and concerned authorities. Last but not least, the limitation and future directions are also documented for further research based on the current study.

Chapter 2

Theoretical Framework and Literature Review

2.1. Theoretical Background

The volatility of stock refers to the investment's behaviour or temperament. Traditional finance theories primarily rely on rationality and perfect market efficiency (Gbeda & Peprah, 2018). However, the limits of arbitrage and bounded rationality become hurdles in market efficiency and optimal decision-making (Shleifer & Vishny, 1997). The following are the main and supporting theories.

2.1.1. Limits to Arbitrage

Limits to arbitrage theory (LOA) are given by Shleifer and Vishny (1997). It states that rational traders normally face restrictions during investment to arbitrate through price inefficiencies. The efficient market hypothesis (EMH) assumes that when there is stock mispricing, a low-risk profit opportunity is created for rational investors, who buy and sell the asset of the same value, pocketing the difference through an arbitrage process.

Suppose a stock falls away from the equilibrium price (becomes undervalued) because of irrational trading (noise traders). In that case, rational investors take a long position while shortening proxy security or other stock with similar characteristics as market movement is why people can make money from stocks. Earlier, supporters of the market efficiency phenomenon believed that prices reflected fundamentals as arbitragers would quickly eliminate mispricing (Douglas, 1968; Hanoch & Levy, 1969).

However, the recent literature (Ganie et al., 2022; Kim et al., 2022; Liu, 2022) has discovered many cross-sectional asset price anomalies. Most of these empirical anomalies result from the arbitrage process. Such an incomplete arbitrage procedure resulted in most of these empirical anomalies, for instance, the IR puzzle. In addition, research in this area is developing and encompassing a wider spectrum, highlighting the impact of financial institutions ' preferences and limits on asset prices. Therefore, examining the importance and implications of arbitrage costs (considered IR) on market efficiency is motivating. Shleifer and Vishny (1997) identified IR as the primary arbitrage cost. Therefore, a risk-averse investor avoids taking a large (short or large) position with high arbitrage risk. Arbitration activity dampens when IR is higher and the capital for this arbitrage process is limited. This leads to a greater divergence from the fundamental value (mispricing) in the current period and higher return predictability (anomaly returns) during the following period. Hence, the theory of limits-to-arbitrage predicts a positive relationship between IR and stock returns as investors demand high compensation for bearing high risks (Arrow, 1996).

Three market participants are involved in the arbitrage mechanism; arbitrageur, noise trader, and investor in arbitrage funds who do not trade with their own. Arbitrageurs are the only specialized trading participants. It is assumed that investors and arbitrageurs are fully rational. The risk-neutral arbitrageur takes the position when the noise trader generates mispricing. Arbitrageurs use their money to allocate funds based on the expected trading returns.

In contrast, investors may rationally allocate money based on arbitrageurs' past returns. When mispricing bet by the arbitrageur, goats against his betters can become more financially constraints when capital is required. Apprehension of this situation will render them more vigilant when participating in their initial transactions, contributing to less efficient market effectiveness (Shleifer & Vishny, 1997). The asset is liquidated reluctantly when this asset's future arbitrator has limited funds, and additional funding is not easily available. As a result, the price fell below its fundamental value. Thus, in extreme circumstances, the arbitrage process does not bring prices close to fundamentals due to the limited resiliency (Stein, 1995). Hence due to costly arbitrage process LOA theory predicts a positive relationship between IR and stock retruns as investors demand high compensation for bearing high risks.

2.1.2. Markowitz Portfolio Theory

Markowitz's portfolio theory (MPT), also known as the modern portfolio theory, was presented by Markowitz (1952). It is the basic foundation of all the theories regarding the risk and returns relationship, which developed in later stages. New principles for measuring risk and using them to choose portfolios are credited to Harry M. Markowitz. He began by considering how risk averse investors are and how they want to maximise projected return with the least amount of risk.

Hence, Markowitz's model provides a theoretical framework for examining risk, return, and the linkages between them. To assess risk and choose investments for a portfolio effectively, he used mathematical programming and statistical analysis. His conceptual framework gave rise to the idea of efficient portfolios. The highest return for a certain level of risk or the lowest risk for a certain level of return are predicted to be produced by an efficient portfolio.

Generally speaking, the risk exposed by individual investment positions is reduced by a diversified portfolio. That said, the portfolio-level risk-return tradeoff also exists. Further, it also documented that diversification lowers IR.

2.1.3. Capital Asset Pricing Models

William Sharpe, an economist and researcher, developed the CAPM model in the first decades of the 1960s. He raised the issue of how risk affected returns, more specifically how risk that couldn't be diversified away. In his book "Portfolio Theory and Capital Markets," published in 1970, he described the capital asset pricing model, which was the result of his study. Sharpe focused on risk diversification, specifically which hazards diversification can address and which it cannot. The CAPM model represents how securities are valued in the financial market in an idealised manner. The standard one-factor CAPM model is developed in the 1960s by Black (1972); Lintner (1965); Mossin (1966); Sharpe (1964), among others. According to their models variance is not changing over time and similarly covariances among stocks also constant.

Two categories of risks are present in the CAPM framework. Systemic risk, sometimes known as market risk, is an example. This is the all-encompassing risk from events that have an effect on the economy as a whole. Inflation, Interest rates, recessions, and geopolitical events like war all have an impact on it. All assets are similarly affected since the systemic risk affects the market as a whole.

Unsystematic risk, usually referred to as firm-specific risk or idiosyncratic risk, is the second type of risk. Each item carries its own specific risk. Individual equities, for instance, are subject to risks from unfavourable company developments that might not affect other peer firms. Unlike systemic risk, this risk is not associated across multiple assets. Diversification or investing in a variety of assets helps lower firm-specific risk; this is the fundamental idea behind MPT. Yet, because it affects all financial assets in a similar way, systemic risk is a harder nut to crack. Based on the CAPM model market risk and how this risk affected on stock values is considered.

Merton created a model of incomplete knowledge that produced a number of market predictions, including the idea that higher-risk businesses generate better profits. By purchasing many equities, risk diversification (as assumed in the CAPM model), which can be very costly when no free information is accessible. Fu (2009) also claims that with time, the arbitrage mechanism vanishes. Investors keep undiversified portfolios as a result, asking for more payoff and risk. According to Schwert (1989), market return variance varies with time. As a result, the model built using time series returns data needs to be modified for heteroscedasticity. Models that take into account the time-varying nature of return volatility therefore offer a more accurate representation of risk than those based on the constant volatility assumption. Heteroscedasticity is another name for this time-varying behaviour of return volatility. The author wants to emphasise that the CAPM, like any model, is built on simplification and makes the model simple to represent reality before moving on to the presentation of the other multifactor CAPM models (Stanculesu, 2016). Although prior studies supported the CAPM, market abnormalities found in the traditional CAPM were interpreted as evidence against the model. For instance, the beta coefficient should result from regressing the excess return (risk premium) of a stock against the market excess return. But it will frequently also result in a recurring problem (alpha). The average excess return obtained over the excess return of an asset with comparable risk is known as alpha, according to Jensen. Since only beta should be able to account for the extra return, the traditional CAPM is unable to do so. Additional anomalies, like as the "small business effect" and the effect of book-to-market value, were discovered in relation to the spread of average returns. Roll (1977) added another criticism, asserting that the market portfolio chosen affects the correlation between beta and the return of an asset or portfolio. Since the criticism contends that the CAPM's single element is insufficient to model and predict returns, a multi-factor approach could alternatively be used.

2.1.4. Multi-Factor Capital Asset Pricing Models

A multi-factor model such as APT theory states the link between the stock returns and macroeconomics variables by considering the systematic risk. In 1976, economist Stephen Ross created the alternative one-factor CAPM model known as the arbitrage pricing hypothesis. The APT theory is based on the assumption that when stock prices occasionally misprice it will revert to fair value and arbitrageurs get the benefit through prices differences. However, this assumption contradicts to the assumption of CAPM one-factor model which assumes that market is fully efficient.

Nevertheless, since investors make directed trades rather than locking in risk-free profits because they believe the model is accurate, this is not an arbitrage operation in the traditional sense. Whereas the APT formula takes into account various aspects, the CAPM model solely takes market risk into account. Furthermore, figuring out how susceptible a security is to various macroeconomic risks requires extensive research. Investors will experience a range of outcomes depending on their selection of the criteria and how many of them are used. (Copeland, Weston, & Shastri, 2005). The current study examines the relationship between risk and cross-sectional expected returns using three-factor, four-factor, and five-factor capital asset pricing models.

2.1.5. Efficient Market Hypothesis

The definition of "market efficiency" states that if the stock price always equals its intrinsic value, the stock market is efficient. Over the years, this definition has become confused with the notion that the market is efficient if investors cannot beat it by earning excess returns. Stock price deviations must be identified to get excess profit and buy(sell) undervalued stock.

The efficient market hypothesis (EMH), the second well-known investment theory, is primarily developed by Fama (1965), and Fama (1970). Essentially, this theory carries the same implication for the stock returns as the random walk. Fame puts forth the basic idea of EMH: virtually, investors cannot beat the market. However, EMH is based on some ideal assumptions about the security market. Among them, one of the main assumptions is that all the relevant information about stock prices is widely, freely, and universally shared among all investors. By explaining the market efficiency concept, Fama (1970) documented three types of information in market efficiency framework namely: weak form, semi-strong form, and strong form. The last type is very strong in term of level of information. It states that all type of information including the insider information reflect in stock prices (Copeland et al., 2005).

Market anomalies of puzzles violate the EMH hypothesis. This implies that all information is not fully incorporated into stock market which opportunities for arbitrageurs for getting abnormal returns which further leads to divergence of stock prices from their fundamental values.

2.1.6. Behavioral Portfolio Theory

In contrast to EMH, investors and traders in the capital market consistently generate superior returns from their investments that beat the overall capital market. The behavioral portfolio hypothesis (BPT) developed by Shefrin and Statman (2000) answers the belief that buyers should eventually be driven to maximize the value of their investments. This implies that buyers have diverse priorities in building an investment portfolio that satisfies a wide range of expectations. It does not obey the same concepts as the capital asset pricing model, the conventional fund approach, and the arbitration pricing method.

Once behavioral finance emanates from continuing, four paradigms preceding it are dismissed. Statman (2010) explained alternative building blocks in behavioral finance. He said that,

1 Investors are normal

2 Market is not efficient

3 Investors make investment decisions based on mental accounting portfolio theory.

4 In the market, book-to-market, market cap, and cognitive biases are the factors that determine stock returns.

In behavioral finance, the price determination process differs from the above scenario. According to behavioral finance, investment decisions are affected by many psychological biases. These are hindsight biases[1] and faulty framing[2] , etc., due to these impediments in processing information that affects investors' decisions. The determined market price in behavioral finance could be different from that price. The current study is also based on the BPT, which describes that investor irrationality and behaviors such as sentiments affect stock returns, lead to market anomalies, and result in abnormal returns (Smith, 2008).

2.1.7. Extreme Value Theory

The extreme value theory (EVT) was pioneered by Tippett (1902 to 1985). Extreme value analysis is used in many disciplines, for example, finance, engineering, earth sciences, etc. EVT is used to discriminate among the return distributions. The return distributions can be differentiated by the tails or the extreme movements in stock prices. In other words, investigating the weight of extreme price movements is the highest existing moment of the distribution of stock market returns.

Significant instabilities in global financial markets have characterized the past few years. This has resulted in numerous criticisms of the current risk. Management systems motivated the search for more suitable methodologies for dealing with rare events with severe consequences. The typical question is: "If things go wrong, how can they go wrong?" The problem is how to model the rare phenomena beyond the range of observations available. In such a situation, relying on a well-founded methodology seems

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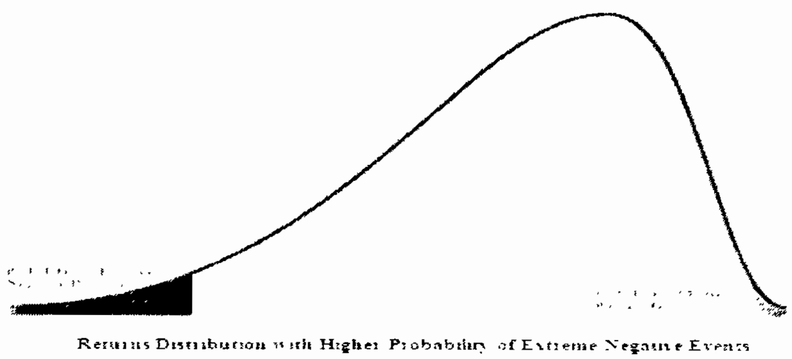
[1] A psychological bias that appears to have been more prevalent in previous events. Due to hindsight bias, an individual may believe an event was more predictable than it actually was.

[2] Faulty Framing bias refers to decision-maker's inclination to be influenced by the presentation of the situation.

essential. Extreme value theory (EVT) provides a firm basis for building statistical models describing extreme events.

There are two approaches to analyzing the extreme value. The first one is the driving block minima (maxima) series in the preliminary step after generating the annual maxima series (Husain & Uppal, 1999) that extracts the annual minima (maxima). The other approach is focused on retrieving the peak values reached at any time during which values surpass a certain threshold (falls below a certain threshold) from a continuous log. This approach is generally referred to as the POT system. A common assumption for the EVT is the spread of poison, using the generic Pareto method for the excesses To fit the distribution's left and right tails using EVT, a body of work was specifically designed to examine the likelihood of low probability but high-risk events (see Figure 2.1). For calculating tail risk, the figure shows the distribution red colour shows the likelihood of extreme negative returns while the green colour shows the likelihood of extreme gains. The central premise behind the EVT is that one of several extreme value distributions can be used to model the probability of observing extreme values (such as negative returns on financial markets).

Figure 2.1: Extreme Negative and Positive Return Distributions



Note: Reported from (Walck, 2007)

Xiong, Idzorek, and Ibbotson (2014) research study attempted to answer the question of which one is being rewarded with left or right tail risk. They claimed that all unambiguous investors view left tail values as bad outcomes, so they should be rewarded, in particular left tail risk, for taking high tail risks. However, they also documented that the right tail risk is penalized assets of non-normal behaviour, so either it's the left or the right tail. These seem to consider equally. So, this study deals with the behaviour of the tails of the stock return series. The study is based on the extreme value risk of the stock market and examines how extreme value theory is used to model extreme events and their associated risks.

In the recent past Value at Risk (VaR) model became very popular as this model can give a single figure that tells about the worst possibility of loss for the given time horizon with a specific confidence interval. As the confidence interval of this model never equals 100%, these models themselves help to indicate the existence of Black Swan events. VaR is "the capital sufficient to cover, in most instances, losses from a portfolio over a holding period of a fixed number of days." VaR models are supposedly there to indicate the occurrence of the Black Swan event. Even the researchers who had predicted the financial crises of 2008 did not use the VaR models for estimation.

The loss associated to the left tail of the return distribution is known as VaR. The value associated with an extremely low percentile of the return distribution, like 1% or 5%, is what this term refers to. VaR's biggest flaw is that it's the most widely utilised method for estimating left tail risk, particularly in the securities market. By applying the extreme value theory, the current study follows a generalized extreme value (GEV) distribution and to create a tail index to measure ITR.

2.1.8. Black Swan Theory

The term Black Swan is popularized by Taleb (2007). It refers to the happening of an event that is very, very rare and impossible to predict. It has a catastrophic nature. The best example of catastrophic ramifications events in finance is the financial crisis of 2008. Black Swan event has a probability of 1 in financial markets, meaning such events are bound to occur. Every 10 to 15 years, such an event always occurs. The frequency and interval depend upon many factors, country-specific, market-specific, firm-specific, and an additional factor of the structure of contracts made in the market.

Nassim Nicholas Taleb analysed and foresaw the financial events in his book "Fooled by Randomness" published in 2001. Another book published in 2007 called "The Black Swan" expanded the metaphor to include practically all significant historical, financial, and scientific breakthroughs. As instances of black swan occurrences, he cited the predictions of the emergence of the internet, World War 1, the personal computer, the dissolution of the Soviet Union, and the 9/11 attacks.

There are white and grey swans, which also present financial risk events and a knowable probability of occurring. The examples of the white swan are a Eurozone recession and a further drop in the Eurodollar exchange rate. The grey swan shades from risk toward uncertainty, but it flits between the black and white swans. It has less likely to happen than a white swan. In other words, at least the probability that it can be estimated accurately is lower, but it has a much higher impact than the white swan (Bogle, 2008).

All kinds of events significantly impact stock and other investment markets. Depending on the Black Swan theory, downturns or market crashes such as the terrible Black Monday, the 1987 stock market crash, or the Web boom of 2000 are relatively predictable. This study tries to anticipate the extreme events during the stock market crises and examine tail risk and jump tail risk puzzles in stock returns.

2.2. Empirical Literature of Idiosyncratic Risk

This section reviews previous empirical studies on IR, tail, and JR. It includes those studies which document the market efficiency hypothesis, random walk hypothesis, and the standard one-factor CAPM model. They also rejected these theories and gave evidence about several abnormalities and IR, ITR, and JR puzzles. In addition, there are some research studies mentioned who tried to solve the IR puzzle. The interaction between stock returns and IR has been subject to extensive empirical investigation, yielding mixed results.

Some earlier studies have found a significant positive association between average returns and IR (Bali et al., 2008; Bali, Cakici, Yan, & Zhang, 2005; Zaremba, 2015). However, some recent studies have documented a negative relationship between IR and expected stock returns (Ang et al., 2006; Babenko et al., 2016; Chabi et al., 2018; Evgeniou et al., 2018; Guo & Savickas, 2006; Yao et al., 2019).

On the other hand, some studies supported the EMH and the standard one-factor asset pricing CAPM model and documented no relationship between IR and expected returns (Bali et al., 2008; Bali et al., 2005; Zaremba et al., 2018). These research studies found highly developed and advanced capital markets for example (Ang et al., 2006; Chabi et al., 2018; Chng, Fang, Xiang, & Zhang, 2017; Stambaugh et al., 2015) for the US stock markets, Guo and Savickas (2006) for G7 countries including the US, Zaremba et al. (2018) for the Eastern European countries, namely; the Czech Republic, Hungry, Poland, Russia, Turkey. Yet, developing and emerging countries still have ignored it.

2.4.1. Positive Relationship between Idiosyncratic Risk and Returns

Investors should be compensated with the high premium due to excessive volatiles. Lehmann (1990) found a significant positive coefficient of IR for the US. He also suggested that residuals from the one-factor CAPM model include variables correlated with non-zero risk premiums and provide two plausible explanations. That is the non-linearity of the residual risk impact and the inadequacy of the statistical methods used to calculate it. While embracing the same notion, Jones and Rhodes-Kropf (2003) have reported that creditors bear IR by demanding a higher premiums for stocks (Barberis et al. (2001). By supporting the Marwistz theory, there are several studies that found a positive relationship between IR and stock returns and gave the justification for high risk and high equity premium (Aabo, Pantzalis, & Park, 2017; Liu & Wang, 2021; Page, Britten, & Auret, 2015; Pontiff, 2006; Tabatabaei Poudeh, Choi, & Fu, 2022; Xu & Malkiel, 2003)

Xu and Malkiel (2003) employed the standard one-factor CAPM model and estimated its residual part as systematic risk and IR. They documented that IR has a positive relationship with average returns. Further, they identified that the market model residual-based should partially reflect exposure to any omitted sources of systematic risk. With the same notion, Similarly, Spiegel and Wang (2006) examined the relationship between IR and the cross-sectional returns by applying standard one-factor CAPM and three-factor Fama and French models and found a positive relationship between the said variables.

Further, Pontiff (2006) highlighted the role of arbitrage limits and explained that holding cost is the biggest cost among the arbitrage costs. The best example is IR, which is particularly misunderstood in empirical research. He also documented that the largest cost of IR is the most arbitrageurs. Furthermore, the portfolio diversification process did not eliminate IR and documented that IR is the largest cost faced by arbitrageurs and demanded high compensation against this holding cost.

By doing comprehensive research on developed and emerging markets, Bartram et al. (2009) documented the market-specific factors related to IR between developed and emerging security markets. They distinguish good volatility as related to developed stock markets and bad volatility as related to emerging markets. They concluded that investors of emerging stock markets demand a high premium as they are more exposed to bad volatility. Another study done by Page et al. (2015) examined IR and the persistence of market anomalies on the Johannesburg stock exchange (JSE). They considered two types of arbitrage cost: a transaction, holding cost, and IR proxies for holding a cost. They investigated whether IR derives the small-size, momentum, and value premium anomalies. They concluded that the value premium reacts positively. Another research on behavioral finance offered a different form of an asset pricing model based on the theory of expectations, where consumers are averse to the volatility in individual stocks. Similarly, stocks with low IR were found to have received higher expected returns (Lee & Li, 2016).

Market anomalies are persistent in firms with high idiosyncratic cash flow volatility documented by Babenko et al. (2016). They examined the relationship between the US's idiosyncratic cash flows and systematic risk. They documented that unpriced cash flow shock entails information about the expected returns. When there is a positive idiosyncratic shock, the decreasing trend of firm-value sensitivity to priced risk factors has been observed. Further, this trend increases IR and firm size.

Moreover, Tuzel and Zhang (2017) examined the relationship between local risk and return using a unique risk-based factor, the industry beta in the US. They documented that location affected the firm risk through local price factors. They found that firms in a higher local beta area had low industry-adjusted returns and conditional betas. This effect is stronger for those firms that have lower real estate exposure.

Further, Aabo et al. (2017) examined the returns variations calculated by absolute IR and confirmed the relationship between IR and mispricing by reconciling the mixed results of prior studies. They found that the variance of residual displays a positive and robust relationship to stock mispricing. The main reason for this phenomenon is the role of noise traders. They found that market volatility is associated with stock mispricing. The level of association between IR and mispricing depends on market volatility. According to Wu, Hao, and Lu (2017), American Depositary Receipt is mispricing due to the total, local and global sentiments and examined the IR in China, Germany, Japan, Hong Kong, and the UK. They find that IR plays a very important role in the mispricing of ADR relative to investor sentiment. More particularly, when the local sentiments increase, the effect of IR on mispricing also increases. However, when there is an increase in global sentiments, then the effect of IR and mispricing decreases. The reason behind the variation effect is possibly due to the different investment preferences of local and global investors.

Along similar lines, Nwachukwu, Tchamyou, and Asongu (2018) explored that when asymmetric information increases, the difference between realized and expected returns has also increased. Information asymmetry follows the same trend as stock volatility. Bartram, Brown, and Stulz (2018) documented that IR increased by increasing the market risk throughout the time frame from 1963 to 2015. This positive relationship holds though out the sample period and under different economic conditions. The reason behind the positive relationship between both IR and MR is the wide economic uncertainty.

Further, this effect is stronger for less liquid firms and still stronger for the most liquid firms. However, firm-specific characteristics cannot explain the relation between IR and MR. Further, Wan (2018) tried to explore IR anomaly through the Min or Max effect in China. He found that this IR volatility anomaly is not due to behavioral bias but is due to limits of arbitrage and strong market frictions with a unique institutional setting in the Chinese stock market.

Another anomaly, namely the buyback anomaly examined by Evgeniou et al. (2018). They found a positive relationship between excess returns and IR due to the announcement's impact (buyback equity issue). They used two models, the three-factor and five-factor, of Fama and French. The main justification of the buyback anomaly is that the action of managers, what managers do, that they buy back the undervalued stock for the benefit of the long-run shareholder at the expense of the short-run investors.

Furthermore, He, Huang, and Zhu (2020) recently looked at the IR puzzle in the Chinese stock market from the standpoint of investors' heterogeneous beliefs. They substituted unexpected trading volume for investors' heterogeneous beliefs. The association between IR and stock performance in the Chinese A-share market is investigated using portfolio management techniques and Fama-MacBeth regression. As an intermediary variable, investors' heterogeneous beliefs positively correlate with IR. The results show that heterogeneous beliefs are efficient intervening variables to explain stock returns and that idiosyncratic volatility is significantly and positively connected.

Vo et al. (2020) investigated the relationship between IR and stock returns with the Vietnam stock market's full-sample and conditional alpha sub-samples. Using the Fama-Macbeth regression method (firm-level analysis) and the sorting portfolio method, they examined the IVOL influence on stock returns (portfolio-level analysis). The IR is estimated via regression using the Fama-French three-factor model, and the Carhart four-factor model. The CAPM model was also estimated using various methods. Their research demonstrates the IR effect, which is thought to be the IR puzzle in subsamples with positive alpha. However, they failed to find any meaningful correlation between full-sample and negative alpha sub-samples.

Recently, Liu (2022) documented that the IR is changing over the time and he invested the relationship between stock return and IR by considering different time horizons. By spliliting the shor-run and the long-run components of IR, he examined the relationship between IR and stock returns. His findings showed that there is a positive relationship between IR and stock return in the short-time horizon because investors may need compensation for taking on IR when dealing with trading turbulence and keeping positions in diverse portfolios. Another recent study by Preeti et al. (2022) also found that IR positively explained the excess returns for energy stocks during the COVID-19 pandemic. They justify this relationship as pessimistic investors who underprice the clean energy stocks. Further, IR has a low level of persistence which may be helpful in stock price forecasting.

2.4.2. Negative Relationship between Idiosyncratic Risk and Returns

There is a massive controversy about the relationship between IR and expected stock returns. The literature mentioned in the previous section found that stocks with high IR have higher expected returns. In contrast, there are several other studies have found that there is a negative association between IR and expected returns for highly developed and advanced capital markets (see, for example, Ang et al. (2006); Chabi et al. (2018); Evgeniou et al. (2018); Qadan and Shuval (2022); Shahrzadi and Foroghi (2022); Yao et al. (2019).

Stocks with the highest IR can experience the lowest returns in the quintile portfolio stock framework examined by Ang et al. (2006). They examined the pricing of aggregate market volatility in expected stock returns in the US. They found that stocks with a high level of sensitivity towards innovations in aggregate volatility have lower mean returns. They cannot explore that this phenomenon is explained by size, liquidity, momentum, book-to-market, and aggregate volatility risk. Cao and Han (2016) used two important measures, arbitrage score and arbitrage cost, to examine the relationship between IR and cross-sectional returns of a stock. They used arbitrage score proxy for stock mispricing and arbitrage cost for IR and found that stock returns increase with IR when stocks are undervalued. In contrast, when stocks are overvalued, the stock returns are decreased with the IR. This cross-section returns and IR relationship are depended on the direction of stock mispricing. They considered IR as an arbitrage cost to get abnormal returns.

Stambaugh et al. (2015) found the beta anomaly in overpriced stocks. They documented a negative relationship between the high beta overpriced stock and the high, leading to excess returns (alpha). The reason behind this beta anomaly is that due to limits of arbitrage, there is low capital available to investors to short overpriced and long underpriced stocks. Verousis and Voukelatos (2018) documented that cross-sectional dispersion reflects the aggregate level of IR in the market as a proxy for IR as a priced state variable. Their objective is to examine whether stock returns are driven by their sensitivity to dispersion. They found similar findings that high sensitivity of IR leads to low returns, and low beta portfolios experience high expected returns. This findings are robust while considering firm-specific characteristics and market conditions.

Further, Bartram et al. (2018) explored the trend of IR historically and found that since 1965 IR has never been lower than in recent years. They documented that IR is 44% lower from 2013 to 2017 compared to 1996 to 2000. The possible justification for this is macroeconomic variables. There have been dramatic changes in the number and composition of listed firms since the late 1990s, and when these listed firms are larger and older, their IR gets lower over time.

Furthermore, Qadan, Kliger, and Chen (2019) have documented the role of IR and stock returns using US data from 1990 to 2016. Their findings show that the increase (decrease) in VIX tends to be followed by a negative (positive) relation, even after other risk factors have been considered. They concluded that an uptick in the VIX, also known as the investors ' fear index, may represent a rise in investors ' risk aversion, causing them to adjust their investments by growing their investment range.

Recently, Yao et al. (2019) tried to price the idiosyncratic skewness, representing gambling preferences. Chinese stock market experiences a significant gambling pricing anomaly "higher idiosyncratic skewness and lower subsequent returns." In addition, they documented that there are two main reasons for the strong gambling atmosphere in China. The first is investors' attention, and trading behaviour is an important gambling driver. The second one is the irrational behaviour of investors, as arbitrage restrictions may further exacerbate the gambling atmosphere. In similar lines, Rao and Zhou (2019) inquired how stock prices affect due to information related to investor sentiments. By dividing the stocks based on high and low price synchronicity, they found that low stock price synchronicity give high returns as compared to high price synchronicity. Further, the relationship between sentiments and returns remained positive and significant and supporting the limits of arbitrage theory.

Poudeh and Fu (2022) analyzed the relationship between stock returns and components derived from the decomposition of stock returns variance at the portfolio and firm levels. The outcomes of the portfolio analysis demonstrate that volatility terms are inversely correlated with anticipated stock returns, with alpha risk having the strongest association with stock returns. On the other hand, at the portfolio level, covariance terms show positive associations with predicted stock returns.

Shahrzadi and Foroghi (2022) also indicate the existence of the IR puzzle by explaining that the left tail risk plays an important role in explaining the IR puzzle. The reason for this is the falling stock price pressure with high left-tail risk on stocks with high unsystematic volatility. Jungmu and Lee (2022) also gave the reason for the occurrence of the IR puzzle. They documented that underperformed firms having high IR leads to the IR puzzle.

Recently, Qadan and Shuval (2022) documented the relationship between stock performance and risk aversion by considering the IR portfolios. They found the evident of the IR puzzle when investors are less averse to risk. However, the IR puzzle is disappeared when there is high level of risk aversion. Another, recent studies documented by Alshammari and Goto (2022) also documented the IR puzzle in Saudi Arabia. They gave the justification that due to high turnover stocks performance are low. Overall, their study confirmed the role of individual stock investor sentiment on security prices. Based on the studies mentioned above, the following hypothesis is developed.

H_1*: There is a negative relationship between idiosyncratic risk and stock returns.*

2.4.3. No Evidence of the Relationship between Idiosyncratic Risk and Returns

While considering the negative or positive relationship between IR and stock return, in existing literature, some studies showed no relationship between them. For instance, Bali et al. (2005) observed that the negative relationship between IR and expected returns for estimating average portfolio returns is not stable under a different weight scheme. They found that when IR sorted quintile portfolios, there was no significant difference between the returns of the equally weighted quintile portfolio. Huang, Liu, Rhee, and Zhang

(2009) studied that the positive returns from a long (short) role in the small (high) IR portfolio were fully explained by an additional control variable, the returns of the portfolio "winners minus losers," added to the traditional three and four Fama and French models. Cross-sectional regressions also confirmed that there is no robust and significant relationship between IR and expected returns once controlled for return reversals. Sun and Wang (2014) and Malagon, Moreno, and Rodríguez (2018) examined the IR and expected returns by incorporating the role of a liquidity shock. They documented that the negative relationship is not pervasive over time. Rather this relationship provides a plausible explanation for its time-varying nature. Further, the liquidity shock has explanatory power for low IR, not for a high IR level. It implies that low IR is priced during the periods following recessions.

Zaremba et al. (2018) explored the relationship between expected stock returns and IR based on stock mispricing in Poland. They documented that the relationship is negative for overvalued stocks and positive for those undervalued stocks. However, their research proved theoretically and mathematically that this relationship is simply a mathematical-driven concept. There is no real anomaly insight in the Poland Stock Market.

Li, Mu, and Qin (2021) demonstrated the significance of economic uncertainty in solving the mystery of the IR puzzle. We discover that idiosyncratic volatility contains information about the state of the economy. Investors that are afraid of uncertainty might help solve the IVOL mystery. Negative IVOL strategy returns only become apparent when there is increased economic ambiguity. Once we limit stock exposure to economic uncertainty, there is no substantial and robust IR puzzle.

2.4.4. Effort to Solve the Idiosyncratic Risk Puzzle

Above mentioned studies explain the negative association of IR and stock returns by telling the IR puzzle. In this section, we documented the studies by some researchers attempting to explain this puzzle. Such as Fu (2009) challenged Ang et al. (2006) research by arguing that IR is time-varying and, therefore, month-lagged value is not a good proxy for the expected value. The author suggested the EGARCH model should be used instead of estimating the expected IR as they are positively related to the expected returns. As pointed out by Fu (2009), the main critique he did on the study was done by Ang et al. (2006) which showed that investor require premium for current risk not historical risk they beard, so analyzing lagged relationships does not make sense.

These different views in economic literature explain the fragility of studies on the relationship between IR and its cross-section variations of returns. The MAX and MIN effects explained the reasons behind this relation. The models that are used produce mixed results. For instance, high MAX stock tends to have a high IR compared to MIN. It implies that, on average, returns are not significantly related to IR. Malagon, Moreno, and Rodríguez (2015) adopted different approaches while analyzing the IR puzzle. First, they considered that investors' behaviour toward a specific investment horizon cause offers a different conclusion to the relationship between cross-sectional returns and IR. They employed WMRA (wavelet multiresolution analysis) this model allows the time series distributions based on different time horizons named time scales, each corresponding to a particular frequency. They observe a positive relationship between IR and returns for investors with the long-run investment horizon and vice versa, indicating that the IR puzzle disappeared as the WMRA scale increased. Chng et al. (2017) tried to answer the question of a difference in hedging and non-hedging stock return while considering the level of IR. They found very interesting results that for those firms who adopt hedging strategies, IR is irrelevant. The reason behind these results is that IR matters when diversification limits exist, but when the firm hedges its operations, IR concern does not matter.

Liu et al. (2019) tried to answer of whether IR should be priced. The existing literature found conflicting results on the cross-sectional relation between expected returns and IR. They found a significant positive relation between IR and expected using the five-factor Fama and French model to estimate IR. When IR was estimated using the GARCH (1,1) model, the favourable correlation vanished. This finding showed that the IR premium is only a surface-level phenomenon; whether IR is significant depends on how we evaluate IR. The result is robust after controlling for investors' lottery preferences, sentiment, and other factors. Kong et al. (2020) documented that corporate social responsibility (CSR) with an emphasis on the environment can effectively reduce information asymmetry by increasing the transparency of investment data. They investigated how ECSR (environmental corporate social responsibility) affects the IR faced by businesses. Their results show that ECSR can dramatically lower the firms' IR using data from A-share listed enterprises in China and data from Rankins CSR Ratings. After several robustness checks, these outcome remains the same. Additionally, conditional analysis results show that state-owned businesses and businesses with weaker external monitoring systems and low internal control are more likely to experience the effects of ECSR.

Additionally, study suggests that firms with high ECSR are more likely to exchange information, which reduces information asymmetry and establishes relationships between

ESCR and firms' IR. Kim et al. (2022) also documented that there is a strong relationship between turnover and IR. Those firms which have high IR have large turnover and this phenomenon is disappeared when turnover variable is controlled in model. Moreover, low returns with high IR and large turnover exclusively during earnings announcement periods. Based on the above research studies, we formulate the following hypothesis.

2.3. Evidence on Tail Risk

The market does not function regularly, as evidenced by a number of crises, including the stock market crash in 1929, Black Monday 1987, the Asia crisis in 1997, the dot com bubble fall in 2000, and the subprime and financial crisis in 2008 (Xiong et al., 2014). Investors require a premium to invest in negatively skewed or left fat-tailed stocks. In the literature we found several studies that show there is a negative relationship exists between ITR and stock returns; for instance, Bollerslev, Li, and Todorov (2016), Chabi et al. (2018), Almeida, Ardison, Garcia, and Vicente (2017), Long et al. (2018), Herliawan et al. (2020), and Deng et al. (2022).

Based on lower partial moments of stock return data, Bali, Cakici, and Whitelaw (2014) created a firm-specific tail risk measure and discovered that it is a poor predictor of future stock returns. The evidence of pricing for negative tail risk was revealed by Bollerslev et al. in 2016. They clarified that taking on negative tail risk has a strong propensity for predicting worse future returns. Similarly. To create a non-parametric tail risk measure, Almeida et al. (2017) used an excess expected shortfall technique that was risk-neutral. They discovered that the risk-neutral tail risk measure had a weak negative predictive ability for intermediate horizon stock returns. Another study by Chabi et al. (2018)

explored the relationship between crash-sensitive stock and their expected returns in the USA. They documented that investors are crash-averse rather than risk-averse, and investors receive higher compensation for holding crash-sensitive stocks. They captured the crash sensitivity using a copula-based approach and found that, on average, lower tail dependence (LTD) stocks have higher future returns than weak lower tail dependence stocks. LTD offers insurance against extremely negative portfolio returns with the view that investors will pay higher prices and eventually accept lower returns for such stocks. Long et al. (2018) explored the ITR puzzle in China, based on EVT they also documented that both cross-sectional and portfolio analysis results show a negative and significant relationship between stock returns and IR in the Chinese stock market. The main justification behind the relationship between tail risk and returns is the high turnover and short sales where individual investors dominate the market.

Chow et al. (2018) introduced a novel methodology to directly determine the tail risk premium for individual stocks and then employed this measure to examine the impact of equity tail risk in the cross-section of stock returns. They found a negative relationship between the equity tail risk and cross-sectional returns. Herliawan et al. (2020) explained that the idiosyncratic tail puzzle in financial crises is due to IR. They also suggested that it should be priced to protect against extreme losses. Further, Ogbonna and Olubusoye (2021) examined the relationship between tail risk and returns. They found that on bad days there is a negative relationship between tail risk and returns.

However, this phenomenon disappears on good days and does not find the IR puzzle. Herliawan et al. (2020) found the ITR puzzle by documenting a significant relationship between ITR and stock returns when the small-cap stocks were removed. They also documented the major reasons cause of ITR puzzle are high investors' emotions, behavioral and psychological biases. The entire network of tail risk spillovers among the most popular cryptocurrencies was built by Nguyen, Chevapatrakul, and Yao in 2020. They recorded crucial network characteristics such as the main currencies that bear the majority of the risk and the main currencies that bear the majority of the risk over time. They discovered that compared to its left tail equivalent, the right tail dependency among cryptocurrencies is substantially stronger. This distinctive quality might have helped cryptocurrencies become more well-liked over the past few years. For Brazil, Freire (2021) calculated the tail risk and looked into the causes of tail risk variance. When there are stock market crashes, financial crises, political shocks, or disaster occurrences like the coronavirus pandemic, the tail risk measure surges. In addition, he discovered that tail risk is countercyclical, has a high capacity for forecasting market returns, and is a poor predictor of actual economic activity. He took the daily headlines from Brazil's major financial newspaper in order to determine the investors' worries about tail risk. The correlation between news and tail risk suggests that fears about disasters, followed by anxiety about the economy and the government, are the main drivers of tail risk variance. While the countercyclical nature of tail risk is explained by economic uncertainty, investors simply need compensation for assuming the tail risk that disaster fears imply. Similar to this, due to the cited catastrophic concerns, tail risk has a detrimental impact on actual outcomes. These results lend support to current models that address asset pricing puzzles involving disaster risk that varies over time. According to Deng et al. (2022), those currencies which have high exposure have low-risk premium. They gave the justification that such currencies are hedged against high tail risk. Moreover, they also documented that option-based tail risk factor is a price factor. A strategy that invests in currencies with high equity tail beta and shorts those with low beta extracts the global component of the tail factor. The estimated price of risk of this novel global factor is consistently negative in currency carry and momentum portfolios, as well as portfolios of other asset classes, indicating that the excess returns of these strategies can be regarded in part as compensations for global tail risk. So the following research hypotheses are proposed based on the above literature.

$\boldsymbol{H_2}$: *Stocks having extreme tail risk provide, on average, lower returns.*

2.4. Evidence on Jump Risk

Jumps or notable discontinuities in price changes are a crucial part of the price dynamics of financial assets (Jiang & Oomen, 2008). Jumps estimation has attracted increased study attention in the wake of the recent global financial crisis (GFC). Large jumps frequently happen concurrently across countries, according to the literature, which increases the connections across global stock markets. (Aït-Sahalia, Cacho-Diaz, & Laeven, 2015; Das & Uppal, 2004). The effects of frequent small jumps and infrequent large jumps on the overall systematic JR are separated by the decomposition of JR into small and large components. Jiang and Yao (2013) observed significant discontinuous shifts in daily stock prices known as leaps and investigated the function of jumps in cross-sectional stock returns. According to their findings, the effects of size and illiquidity are entirely accounted for by cross-sectional differences in jumps in small and illiquid stocks, which have greater jump returns. Jumps also take the value premium into account based on value-weighted portfolios. Moreover, momentum or net share issue effects are not caused by jumps.

Arouri et al. (2019) decomposed systematic risk into continuous and discontinuous parts and jump systematic risk into negative and positive, small and large components and examined their relationship with equity returns in major equity markets. The findings shown that the movement of developed equity markets with market index are more associated than the less developed or emerging markets. In pre-crises time period, the returns for downside and continuous JR is positive while during crises the reward is negative.

Another study by Ebrahimi and Pirrong (2020) The risk premium associated with large upside jumps in the oil market has been documented as a significant driver of the cross-section of stock returns. In contrast to previous research, variance risk is only priced when jumps are not controlled for. Price increases are priced in times of tight supply-demand conditions but not in times of abundant supply. There is evidence that downward jumps are priced in times of abundant supply but not in times of scarcity. Risk-neutral jump innovations have predictive power for important economic indicators, most notably consumption growth. This helps to explain JR's pricing.

Odusami (2021) examined JR in the Real Estate Investment Trust time series (REITs). In their study, the econometric model incorporates jumps into the volatility forecast by estimating jump-augmented Heterogeneous Autoregressive (HAR) models of realised volatility using high-frequency index-level and firm-level data. The forecasting accuracies for generating one-step ahead daily Value-at-Risk are compared with those generated from historical returns, the bootstrap technique, and the severity loss distribution to assess the information value of these specifications. Leong and Kwok (2022) investigated risk pricing in the context of cryptocurrency returns. They separated jumps from diffusive variations by decomposing total variations into systematic and idiosyncratic components. According to the findings, a hedged portfolio sorted on idiosyncratic diffusive risk yields a weekly return of -2.16%, indicating the presence of a low IR anomaly. They then investigated potential explanations for this anomaly, discovering that arbitrage limits prevent arbitrageurs from fully correcting the mispricing.

Carverhill and Luo (2022) studied JR over time in order to model stock price dynamics and cross-sectional option prices. Using two independently evolving processes, they investigate jump-diffusion specifications for stochastic volatility and jump intensity. They explicitly imposed time-series consistency in model estimation using a Markov Chain Monte Carlo method. They discovered that the jump size and standard deviation of jump size premia are more prominent under time-varying JR. Simultaneous returns and increases in volatility aid in reconciling the time series of returns, volatility, and jump intensities. Finally, independent time-varying jump intensities improve cross-sectional fit of option prices, particularly at longer maturities.

Pricing of jump in cross-sectional return is very important as high jump volatility betas have a negative relationship with high jumps and bond returns. They also showed that when there is a low rating of bonds, a high frequency of high jumps is observed. They also documented that crisis jumps are significant compared to volatility, and co-skewness, co-kurtosis, and downside risk cannot explain the JR (Chen et al., 2022).

H_3: *Stock with jump risk provides lower returns.*

2.6. Determinants of Idiosyncratic Risk

Previous studies in IR have focused more on the perspective of asset pricing, and most studies in this area find that IR is priced for returns of risky assets (Qin & Zhou, 2019; Zaremba et al., 2018). However, very limited studies have investigated what factors/variables explain IR and which factors drive IR is still not clear. Several factors have been identified that play an important role in investigating IR to examine the determinants of the firm's IR. Following is the detail of the determinants of the choice factors by following the existing literature.

2.6.1. Firm Size

Firm size is an important variable that significantly affects firms' IR. Firm size plays a vital role in firm performance. Generally, higher human and financial resources enable firms to absorb different risks. Large-sized firms not only have more ability to afford risks but also bear fewer risks than small- and medium-sized firms (Hirsch & Adar, 1974). The size effect was first tested by Banz (1981). He examined the empirical relationship between returns on common stocks and total market value. He found that smaller firms (smaller firms) have higher risk-adjusted returns on average than larger firms. Later, this negative relationship is also documented by many other studies. For example, Faff (2001) showed a strong negative relationship between IR and firm size in the Australian stock market. Kumari et al. (2017) also found a negative relationship between IR and firm size.

Moreover, recent studies also found the same results indicating that the negative relationship between firm size and IR is much greater for businesses having small firm sizes than large size businesses (Ozdemir, Erkmen, & Kim, 2020). Another recent study by He, Qin, Liu, and Wu (2022) also documented the negative relationship by showing the correlation measure. The following hypothesis is tested based on the studies mentioned above.

H_4: There is a negative relationship between firm size and idiosyncratic risk.

2.6.2. Return on Equity

Equity return is one of the investors' most popular profitability ratios to determine stock prices (Jiang & Oomen, 2008). The role of ROE cannot be ignored in determining stock prices. Evidence from previous studies supports the relationship between IR and ROE. For instance, Wei and Zhang (2006) found a negative relationship between ROE and volatility of stock returns in the USA. Moreover, Brown and Kapadia (2007) found that newly listed risky firms drive the rise of IR in the US market. They also documented that newly listed firms are smaller in size, have lower profitability, are unlikely to pay dividends, have more fractions of intangible assets, and are highly likely to be growth stocks. Kumari et al. (2017) also documented the negative relation of ROE with their respective IR of stock prices. Bartram et al. (2018) also documented that firm stock volatility is negatively related to return on equity (ROE). They found that the upward trend in average stock return volatility is fully accounted for by a downward trend in ROE and an upward trend in the volatility of ROE. Ceylan (2021) examined the impact of firm-specific and macro factors with financial distress risk measured through IR and found that when financial distress increase, return on equity is decreased. Izcan and Bektas (2022) also document negative relationship with the IR of banks for medium- to high-risk levels

H_5*: There is a negative relationship between return on equity and idiosyncratic risk.*

2.6.3. Dividend Yield

According to the dividend signing theory, dividend yields signal firms' prospects. The dividend signaling theory suggests that increases in dividend yields may indicate management's optimistic expectations of future earnings and the company's risk profile. According to Hashemijoo, Ardekani, and Younesi (2012), there is a negative link between share price volatility and dividend yield and payout. Anwar, Singh, and Jain (2015) concluded by showing that the announcement of cash dividends tends to reduce stock return volatility. According to Arslan, Zaman, and Phil (2014), firms that issue cash dividends have lower stock return volatility. They also documented that dividend-paying firms have good financial conditions and are unlikely to face instability or insolvency. Mehmet (2019) also found a negative relationship between IR and dividend yield. The justification is that according to the dividend theory, dividend growth yields signal good news and vice versa. Therefore, it is likely to expect a negative relationship between dividend yield and IR as firms with better prospects should have lower firm-specific risk or IR (Rajverma, Misra, Mohapatra, & Chandra, 2019). According to Firmansyah, Sihombing, and Kusumastuti (2020), firms that pay dividends will be less volatile compared to non-paying dividend firms. Another study by Izcan and Bektas (2022) found a negative relationship between DY and IR and documented that DY negatively correlates with the medium and high levels of IR for financial firms. (Li, Liu, & Ni, 2021; Poudeh & Fu, 2022) also documented that while compared to low dividend paying firms, they discovered that large dividend paying firms experience a reduction in IR. Based on the existing literature, we formulate the following hypothesis.

H_6: *There is a negative relationship between dividend yield and idiosyncratic risk.*

2.6.4. Leverage

According to Myers (1977), debt and IR have a positive relationship. He argued that large business risk could reduce the agency cost of the debt, which causes a firm to use more debt in its capital structure. Several other research studies, such as Campbell and Hamao (1992), Kale, Noe, and Ramirez (1991), and Kim and Sorensen (1986), found that when business risk increases, firms restructure their capital by increasing debt. Further, Müller (2008) found that exposure to IR increases equity capital costs and makes bank borrowing more attractive. In the research study of Acharya, Gujral, Kulkarni, and Shin (2011), it is found that firms' IR increases as dividend yields rise. One of the justifications is that the financial institutions continued to pay dividends out of liabilities, which led to increased leverage. As leverage increases, these financial institutions are expected to increase their IR.

According to Hsu and Huang (2016), firm leverage increases IR. They justify their findings by stating that the increased leverage because of share repurchases increases businesses' exposure to IR, thus boosting stocks' anticipated returns. The study of Haque and Nasir (2016) also indicated high volatility of banks due to low liquidity, high leverage, and strong regulatory influence. Moreover, Hsu, Fournier, and Srinivasan (2016) and Sun and Govind (2017) also found a negative relation between leverage with

IR. In contrast, recently, Barattieri, Moretti, and Quadrini (2021) also documented that non-core funding provides insurance against IR faced by banks. Insurance makes leverage and investment more attractive, but it also increases the banking sector's vulnerability. We formulated the following hypothesis based on the above literature.

H_7: *There is a positive relationship between leverage and idiosyncratic risks*

2.6.5. Liquidity

According to Falkenstein (1996), investors preferred liquid stocks. The rationale is that large institutional investors manage large portfolios, and the increased liquidity enhances their trading capacity while minimizing the price impact of large trades. A positive relationship is found between total volatility aggregate and stock turnover (Glaser & Weber, 2003; Schwert, 1989). Amihud (2002) also documented that expected market liquidity positively affects stock excess return over time, suggesting that an excess stock return is partly a liquidity premium. They also found a negative relationship between stock returns over time and unexpected contemporary illiquidity.

Moreover, according to Dinh (2017), the effect of liquidity on IR is stronger than systematic risk. Their results suggested a positive relationship between liquidity and IR in high-frequency trading stocks compared to low-frequency trading stocks. Malagon, Moreno, and Rodríguez (2018) have investigated the liquidity shocks effect on high and low IR stocks and concluded that liquidity shocks on high idiosyncratic volatility stocks during recessions are much bigger. Along similar lines, Kumar and Misra (2019) explored that liquidity forms part of the systematic risk and IR, and it is a source of priced systematic risk and IR in stock returns. Yun, Cho, and Park (2021) suggested that there is a significant impact of liquidity risk on stock returns, and firm liquidity also increases the firm's specific risk. In contrast, a negative relationship exists between liquidity and IR for financial firms by providing the justification that the riskiness of the banks increases, and a stronger relationship is detected (Izcan & Bektas, 2022). Based on this literature, we formulated the following hypothesis:

H_8: *There is a positive relationship between liquidity and idiosyncratic risk.*

2.6.6. Momentum

This phenomenon applies to the most overwhelming anomalies ever (Jegadeesh & Titman, 1993). Prior literature has found a positive relationship between IR and stock returns. For example, Asness, Moskowitz, and Pedersen (2013) found that momentum returns are higher among high IR, especially high IR in losers stocks. Further, Pyo and Jae Shin (2013) confirmed the IR effect on momentum returns by illustrating a positive time-series relationship between momentum returns and aggregate IR. Cheema and Nartea (2017) documented that momentum has no positive relationship with IR.

Further, the research done by Novy-Marx and Velikov (2016) and Asvathitanont (2018) found that momentum can be positively and negatively correlated to IR due to transaction costs. Furthermore, Kumari et al. (2017) found that momentum is a very important determinant of IR as it is strongly positively related. Based on prior research studies, the study uses the momentum factor as the determinant of IR, which is an entirely new facet. Ahmed and Alhadab (2020) examined the relationship between idiosyncratic risk and momentum return by considering high-tech and low-tech firms. They did not find any statistically significant relationship between high-tech firms and IR. However, a significantly negative relationship is found for low-tech stocks with IR. Recently, Zareei

(2021) and Barik and Balakrishnan (2022) found a positive relationship between momentum and IR. They documented through empirical results that IR has a significant impact on the momentum effect of both short-term and long-term trading strategies, as the resulting alphas are non-zeros and statistically significant. We formulate the following hypothesis.

H_9: *Momentum is positively linked to idiosyncratic risk.*

2.6.7. Market Power

Market power (competitive position) is used to hedge and smoothen the cash flow volatilities resulting from the IR. There is a significant influence on a firm's competitive positioning due to IR. Businesses operating in highly competitive markets have little IR, which has led to strong firm performance in terms of returns (Vuolteenaho, 2002). Very little literature directly examines market power as the determinant of IR. Gaspar and Massa (2006) confirmed the link between stock performance and a firm's competitive environment through IR. They documented that firms with high market power or established in concentrated industries have lower IR. Another study by Abdoh and Varela (2017) documented that firm-specific risk is more affected when there are many rivals in the market. They found that market competition increases IR relative to market risk.

Chortareas, Noikokyris, and Rakeeb (2021) documented that corporate investment of firms with low market power and market share responds positively to IR. However, a high degree of market power moderates this positive relationship, allowing for delayed investment under uncertainty. Further, Aziz, Rahman, Hussain, and Nguyen (2021) documented that the nexus between green performance and firm-specific risk is moderated by market power and industry competitive intensity. They analyzed that firms with higher green performance are at lower IR through the market power mediation effect. Thus, based on the above findings, the following hypotheses are made.

$\boldsymbol{H_{10}}$: *Market power is negatively linked to idiosyncratic risk.*

2.6.8. Price-to-Earnings Ratio

The price-to-earnings ratio (P/E) is crucial in the stock valuation process. It helps to determine whether the stock is overvalued or undervalued (Bhootra & Hur, 2015). We hardly find few studies on the P/E ratio determinant of IR. The first study on the Australian Stock Market examined the relationship between the P/E ratio and IR using portfolio and regression analysis. They found that big firms have a high P/E ratio and a negative relationship with IR (Liu, Di Iorio, & De Silva, 2016). Another study by Kumari et al. (2017) examined the indirect relationship of the P/E ratio with IR via mean returns using portfolio analysis. They found that a high P/E ratio has low mean returns, which is also called the IR puzzle, resulting in high IR. Suyanto and Sibarani (2018) also examined the effect of the E/P ratio on IR and documented that, on average high P/E stocks have low IR. Recently, Firmansyah et al. (2020) found that the P/E ratio is a significant determinant of IR in the banking sector. Based on these findings, we formulate the following hypothesis.

$\boldsymbol{H_{11}}$: *Price-to-earnings ratio is negatively linked to idiosyncratic risk.*

2.7. Deficiencies in the Existing Literature

According to the LOA theory, investors cannot fully diversify their portfolios. Based on the studies mentioned above, the main concern is to examine the IR, ITR, and JR puzzles. To existing literature, mixed results for the relationship between risk and cross-sectional returns were discussed extensively and are still debatable. Furthermore, existing literature on developing and emerging countries are ignored where the magnitude of bad volatility and information asymmetry prevails, and law and regulation about investors' protections are weak.

Based on the studies mentioned above in the literature review sections, our research differs from the existing studies in the following ways. First, the main concern is examining the IR, ITR, and JR puzzles in the top emerging (BRICS) and developing countries like Pakistan, which were previously ignored. Further, our study also examines these puzzles in different groups of firms based on their fundamentals, which was also not done before.

Secondly, no study is available which examines the drivers of IR. Along similar lines, exploring the determinants of IR based on different groups of firms also differentiates our study from the existing literature. Thirdly, the study examines the ITR and JR puzzle by considering the relationship between upper and lower tail risk and positive and negative jump risk with stock returns is not available in the existing literature. In addition, examining tail risk and JR is a very interesting research topic along with the IR puzzle by applying the latest and most sophisticated technologies, such as quantile regression, instead of ancient ones, which have many flaws and disadvantages stated in the existing literature.

Fourthly, market anomalies cast doubt on the capital asset pricing models. Hence, there is a dire need for a factor proxy for IR. Thus, the current study introduced a modified arbitrage score factor in the five-factors CAPM model to price the IR, which is not done in existing research.

Chapter 3
Data and Methodology

3.1. Introduction

This section comprises research design, data description, and detailed methodology to analyze IR, ITR, and JR puzzles of all non-financial firms in Pakistan and BRICS member countries. First, this section started by explaining the measuring of IR and its determinants. Besides, for a deep analysis of the IR puzzle, this study also presented a detail procedure about the portfolio construction. The next is to examine the IR puzzle by employing the standard one-factor, three-factors, four-factors, and five-factors CAPM models and their descriptions are documented. Further, this study also propose an arbitrage score factor for IR pricing by considering several new factors.

Moreover, a recent phenomenon of JR and ITR and its construction procedure is also discussed. In addition, in-depth analysis the study split the sample of non-financial firms into non-overlapping different groups and examined the said puzzles for each group. The detailed procedure of measuring the firms into different categories is also given.

3.2. Sample and Data Source

This study considers unbalanced panel data on all nonfinancial firms listed on the major stock exchanges of BRICS countries, namely, the Shanghai Stock Exchange (China) National Stock Exchange (India), Johannesburg Stock Exchange (South Africa), Sao Paulo (Brazil), and Moscow Stock Exchange (Russia). Financial firms are excluded because their capital structure and liabilities differ substantially from those of nonfinancial firms. All daily stock prices and balance-sheet data are taken from Thomson Reuters Financial DataStream. Three-month Treasury-bill rate data are taken from the International Monetary Fund (IMF) International Financial Statistics database. The study covers the period 2000 to 2019, with 1578 firms for China, 280 for Brazil, 859 for India, 291 for South Africa, and 375 for Russia are included in this study. The selection of any specific firm in any specific sector was made with no specific criteria. However, we included firms with at least eight days in months of trading. The reason to exclude firms with less than eight days of trading is to reduce the impact of infrequent trading in IR estimation.

3.3. Variables Measurements

3.3.1. Stock Returns

Daily stock prices are used to calculate stock returns. The idea of calculating the stock returns is taken from the study of Fong, Wong, and Lean (2005) and Rashid and Kausar (2019).

$$R_{id} = ln(P_{id}/P_{id-1}) \tag{3.1}$$

where

R_{id} is the stock return of i^{th} stock at day d

P_{id} is the current stock price of i^{th} stock at day d

P_{id-1} is the lag value of i^{th} stock at day d-1

There are two major reasons for using log returns. First, they are addictive and can add log returns but cannot add simple returns. Said differently, to add the returns, the researcher must compound them. The second reason is the log normality (Copeland, Weston, & Shastri, 1988).

3.3.2. Measuring Idiosyncratic Risk

The idea of measuring the IR is taken from the study done by Ang et al, (2006). IR of stock i is obtained from the following time-series OLS regression (equation 3.2) by regressing the daily excess stock returns during the month on the contemporaneous Fama-French market, size, and book-to-market factors. IR of stock i in month m is the standard deviation of the residuals ($\varepsilon_{i,d}$) obtained by estimating the equation. This month vice standard deviation of daily estimated residuals for each firm is used as a proxy for IR ($\widehat{IR}_{i,m}$).

$$R_{i,d} - R_f = \alpha_i + \beta_{i,MRT} (MRT_d - R_f) + \beta_{i,SMB} SMB_d + \beta_{i,HML} HML_d + \varepsilon_{i,d} \quad (3.2)$$

where $R_{i,d}$ is the daily excess return of stock i at day d and α_i represents the intercept or abnormal returns of stock i at day d. MRT is the value-weighted excess return of the market portfolio. SMB is the difference between the return on a portfolio of small stocks and the return on a portfolio of big stocks ranked by market capitalization. HML is the portfolio's return that goes long on the top third of firms with the highest book-to-market ratios and shorts the bottom third of firms with the lowest book-to-market ratios.[3] The $\beta_{i,MRT}$, $\beta_{i,SMB}$ and $\beta_{i,HML}$ are the coefficients of MRT, SMB, and HML, respectively.

3.4. Methodology

To examine the IR puzzle, we first perform portfolio analysis using the parametric approach, t-test (le Cessie, Goeman, & Dekkers, 2020), and non-parametric, stochastic

[3] Market, Size, and Value portfolios are constructed based on the excess market returns, market capitalization, and book-to-market ratio data are taken from the Thomson Reuters Financial DataStream.

dominance (Larsen & Resnick, 1993) approach as a preliminary analysis. To examine the IR, ITR, and JR puzzles, we employ quantile regression (QR) and OLS regressions for comparison with the QR results. Next, to examine the determinants of IR, the detail of the fixed effect model is given. After that, the detail of arbitrage score factor is given to price IR.

3.4.1. Parametric Approaches

3.4.1.1. *T*-test

By following the studies of Long et al. (2018), we first sort the firms into quintile equal-weighted and value-weighted portfolios ranked by their respective IR and Size. IR1 contains firms with the lowest *IR*, while IR5 contains the highest *IR*. Similarly, SIZE1 (SIZE5) contains firms with small (large) market capitalization. Next, we apply the *t*-test (Newey & West, 1987) to check the mean difference of these extreme portfolios and examine the IR puzzle.

3.4.1.2. Capital Asset Pricing Models

In addition, this study also uses the standard one-factor, three-factor, four-factor, and five-factor CAPM models. It estimates the values of alphas (abnormal returns) to identify IR puzzles based on quintile portfolios of IR. After estimating these multi-factors in CAPM models, the estimated alpha values are presented. If the alphas are statistically significant, then one can conclude that the IR puzzle is present. The following are the models:

$$R_{i,m} = \alpha_i + \beta_{i,MRT}\, MRT_m + \varepsilon_{i,m} \tag{3.3}$$

$$R_{i,m} = \alpha_i + \beta_{i,MRT}\, MRT_m + \beta_{i,SMB} SMB_m + \beta_{i,HML} HML_m + \varepsilon_{i,m} \tag{3.4}$$

$$R_{i,m} = \alpha_i + \beta_{i,MRT}\, MRT_m + \beta_{i,SMB} SMB_m + \beta_{i,HML} HML_m + \beta_{i,MOM} MOM_m + \varepsilon_{i,m} \quad (3.5)$$

$$R_{i,m} = \alpha_i + \beta_{i,MRT}\, MRT_m + \beta_{i,SMB} SMB_m + \beta_{i,HML} HML_m + \beta_{i,RMW} RMW_m + \beta_{i,CMA} CMA_m + \varepsilon_{i,m} \quad (3.6)$$

where $R_{i,m}$ is the excess return for stock i at month m, and MRT_m is the value-weighted excess market index return at month m.

SMB_m (small minus big) is the difference between the return on small and big firms at month m. It is the average return on the nine small stock portfolios minus the average return on the nine big ones. While HML_m (high minus low) is the difference between the returns of high book-to-market and low book-to-market firms on month m. It is the average return on the two value portfolios minus the average return on the two growth portfolios.

MOM_m (up to minus down) is the momentum factor computed on the differential between a portfolio of winners and a portfolio of losers returns on month m. It is calculated by subtracting the equal-weighted average of the lowest-performing firms from the equal-weighted average of the highest-performing firms, lagged one month. RMW_m is the profitability factor that is the difference between the return on the stocks with robust and weak profitability at month m. It is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios.

CMA_m is an investment factor that is the difference returns of low and high investments, which can be called conservative and aggressive stocks at month m. It is the average return on the two conservative investment portfolios minus the average return on the two aggressive ones.[4]

3.4.1.3. Non-Parametric Approach: Stochastic Dominance

After discussing the parametric approaches, we also apply the non-parametric stochastic dominance, KS type test (Barrett & Donald, 2003) to examine IR puzzle on extreme portfolios. The SD approach is generally used to test whether one series stochastically dominates the other at any specific stochastic order. This study tests whether the highest EW (VW) portfolios dominate over the lowest EW(VW) return portfolios using the first three SD rules. These rules are the first-order stochastic dominance (hereafter, FSD), the second-order stochastic dominance (henceforth, SSD), and the third-order stochastic dominance (henceforward, TSD). To explain the SD rules, let's assume A and B are the two portfolios with stochastic outcome return (say "*r)*".

Let $\{A_i\}$, where $i = 1, 2, \ldots, N$ be *i.i.d* (identical independent distribution) sample of portfolio returns to dominated distribution having the $F_A(x)$ cumulative frequency distribution. By assuming that the CDFs generally lie between [0, x], where $x > 0$ and are continuous functions between the space [0, x], we define the following rules to explain whether the function $D_A^s(x)$ integrates $F_X(\mathrm{r})$ to any stochastic dominance order $s = i$.

$$D_A^1(\mathrm{x}) = F_A(x) \qquad \text{For FSD} \qquad (3.7)$$

$$D_A^2(\mathrm{x}) = \int_0^x F_A(u)du = \int_0^x D_A^1(u)du \qquad \text{For SSD} \qquad (3.8)$$

[4] The standard one-factor CAPM was introduced by Treynor (1961, 1962)[4] Sharpe (1964), Lintner (1965) and Mossin (1966) independently, building on the earlier work of Harry Markowitz on diversification and modern portfolio theory. The three-factor and five-factor models are presented by Fama (1995); Fama and French (1993) Fama & French, 1993, 2015 respectively. The carhart model is presented by Carhart (1997).

$$D_A^3(\mathrm{x}) = \iint_0^x F_A(v)dvdu = \int_0^x D_A^2(u)du \qquad \text{For TSD} \tag{3.9}$$

Similarly, let suppose $\{B_i\}$, $i=1,2,...,N,$ be *i.i.d* sample of portfolio returns to non-dominated distribution with CDF of $F_B(x)$. Next, we define the distribution of $D_B^s(x)$ for the function $F_B(x)$ as similar as already done to define $D_A^s(\mathrm{x})$. Therefore, the test has the following null and alternative hypotheses to test the stochastic dominance order of portfolio "*A*" over portfolio "*B*":

$H_0^s : D_A^s(\mathrm{x}) \leq D_B^s(\mathrm{x})$ for all x (x is a series of portfolio returns)

$H_1^s : D_A^s(\mathrm{x}) > D_B^s(\mathrm{x})$ for some x

The following KS test statistic is applied to test the null hypothesis, H_0^s.

$$K_s = (\frac{N^2}{2N})^{1/2} \frac{sup}{x} [D_A^{-s}(x) - D_B^{-s}(x)] \tag{3.10}$$

This test can be applied for the second (s = 2) or higher orders (s > 2) of SD. To estimate the value of suprema of test statistics, K_s (Barrett & Donald, 2003), we obtain the p-values for the underlying null hypothesis through the simulation method.

3.4.1.4. Quantile Regression

To examine the existence of the IR puzzle, the current study applies quantile regression (QR) in addition to portfolio analysis. QR regression estimates the conditional median of the target. QR is a type of linear regression employed when the linear regression requirements are not met (i.e., independence, homoscedasticity, linearity, or normality).

Under QR, the study uses the percentile method proposed by Koenker and Hallock (2001) to construct confidence intervals for each parameter in δ_i, where the intervals are computed from the empirical distribution of the sample of the bootstrapped estimates. This approach is suitable because the traditional method like OLS fails to address the behaviour in both (upper and lower) tails of the stock return distribution. Therefore, this study first applies the QR regression to check the non-monotonic relationship between IR and stock returns. The QR regression takes the following form.

$$R^q_{i,m} = \delta^q_i + \delta^q_{i,\widehat{IR}} \widehat{IR}_m + \delta^q_{i,REV} REV_m + \delta^q_{i,Mom} Mom_m + \delta^q_{i,MB} MB_m + \delta^q_{i,DS\_CK} DS\_CK_m + \delta^q_{i,Beta} Beta_m + \varepsilon^q_{i,m} \tag{3.11}$$

where $\delta^q_i = 20\%, 40\%, 60\%, \ldots\ldots\ldots, 80\%$. $R^q_{i,m}$ denotes the stock return of i^{th} firm at month *m*. δ^q_i represents the constant term. $\widehat{IR}_m$ denotes IR of i^{th}, firm at time *t* estimated from the equation (3.2). REV_m is the stock return of the previous month. MB_m denotes the market value of equity divided by the book value of equity i^{th}, the at month *m*. Mom_m the stock return of the previous year excluding the most recent month of i^{th}firm at month *m*. DS_CK_m and $Beta_m$ are the downside co-skewness and systematic risk of equity i^{th}, the at month *m*. $\delta^q_{i,\widehat{IR}}$, $\delta^q_{i,REV}$, $\delta^q_{i,MB}$, $\delta^q_{i,Mom}$, δ^q_{i,DS_CK}, and $\delta^q_{i,Beta}$ are the coefficients of measuring the effect of stated variables. $\varepsilon^q_{i,m}$ represents the error term, assuming it follows the identical independent distribution *(i.i.d)*.

3.4.2. Determinants of Idiosyncratic Risk

To achieve the third objectives, the fixed effects static panel data model would be selected by applying Hausman (1978) test to examine the determinants of IR determinants. Precisely, the following regression model is estimated.

$$IR_{i,t} = \beta_i + \beta_1 Size_{i,t} + \beta_2 Leverage_{i,t} + \beta_3\, Market\ Share_{i,t} + \beta_4 Liquidity_{i,t} + \beta_5 MOm\ Return_{i,t} + \beta_6 ROE_{i,t} + \beta_7\, P/E_{i,t} + \beta_8 DY_{i,t} + \varepsilon_{i,t} \tag{3.13}$$

where $IR_{i,t}$ is the estimated IR (from Equation (3.2) and then annualized) of $the\ i^{th}$ firm at year *t*. $Size_{i,t}$ is the natural logarithm of the sales of the i^{th} firm at year *t*. $Leverage_{,t}$ is the ratio of long-term debts over total assets of i^{th} firm at year *t*. $Market\ Share_{i,t}$ is the proportion of the industry represented by a single firm, divided by firm sales with the industry sales of i^{th}firm at year *t*. $Liqudity_{i,t}$ is the annual average of the monthly turnover ratio (the number of shares traded to the number of shares outstanding of i^{th}firm at year *t*. $Mom\ Return_{s,t}$ is the cumulative return of a stock in *t* − *12* through *t* − *2*. We skip one month between portfolio formation and the holding period to avoid the effects of the bid-ask spread, price pressure, and any lagged reaction. $P/E_{i,t}$ is the stock price to earnings ratio of i^{th}firm at year *t*. $DY_{i,t}$ is the dividend yield of i^{th}firm at year *t*. $\varepsilon_{i,t}$ is the residual of i^{th}firm at year *t*.

The second objective of our study is to explore the driving factors or determinants for IR. Previous research studies have been documented several determinants for developed stock markets. For instance, such as future earnings growth rate, firm age, profitability ratios, and risking firms newly listed at the stock exchange are considered the determinants of IR. For example, Xu and Malkiel (2003) found that future earning is positively related to IR in the US. They explained that profitability ratios are the fundamental factors of IR in the Japan stock exchange.

In order to examine the determinants of IR, the static panel data model's specifications would be appropriate. Using OLS regression based on the assumption of independent and identically distributed (i.i.d) error terms could be misleading, and OLS is likely to be inefficient relative to an estimator that exploits the serial correlation. An attractive feature of the panel data model captured both the time series and cross-sectional effects. However, since it has been repeatedly observations of the same units, the standard assumption of independent observations may no longer be appropriate. Since such data involve both cross-sectional and time dimensions so, cross-section data (heteroscedasticity) and time series (autocorrelation) problems need to be addressed.

For static panel data modeling, there are three basic options to estimate the model, namely: the pooled OLS model, fixed effects model (FEM) and random effects model (REM). In the pooled OLS model, no endogeneity is assumed and all the entity-specific characteristics are examined in one regression framework that means individual-specific characteristics do not matter. However, in FEM the intercept of the regression model is allowed to differ among individuals in recognition of the fact that each individual or cross-sectional unit may have some special characteristics of its own (Gujarati, 2009). The assumption of zero correlation between the unobserved effects and the explanatory variables may be restrictive. This is addressed in the FEM by including individual-specific intercepts, which capture all time-invariant differences across individuals so that the error term can be assumed to be *i.i.d* over individuals and time (Verbeek, 1990). On the other hand, REM is assumed that the intercept of an individual is a random drawing from a much larger population with a constant mean value. Following is the detailed procedure to do choice among pooled OLS, REM, and FEM.

First, the researchers have to do a choice between pooled OLS and REM. For this, Breusch and Pagan (1980) test would be applied. The null hypothesis of Breusch and Pegan (BP) test is as follows:

$$H_0: \sigma_\mu^2=0 \text{ there are no random effects}$$

If the null hypothesis would be rejected by using the BP test this implies that individual-specific effects exist and the pooled OLS regression would be inappropriate. In the second step, the researchers have to choice between REM and FEM. For this, Hausman (1978) test would be applied. The null hypothesis of the Hausman test is as follow:

$$H_0: \text{ the random effect is appropriate}$$

The p-value of the Hausman test indicates whether the REM is preferred over FEM or not. However, for this selected model, the firm-fixed effect is more appropriate in the sense because in these models the values of independent variables are assumed to be fixed or constant and only the dependent variable changes in response to the levels of independent variables. Said differently, it fixes the effect of the omitted variables that are constant throughout the sample period for a given time or omitted variables that may change for a firm over time but are constant for all firms over a given period. For instance, the investors' sentiments variable is absorbed as a fixed effect and is not bias the results. The null hypothesis is that the preferred model is random effects, and the alternate hypothesis is that the model has fixed effects.

3.5. Measuring of Arbitrage Score Factor and Pricing of Idiosyncratic Risk

Once the researcher examines the IR risk puzzle and its determinants, the fourth and fifth objectives are to construct a single modified arbitrage score factor based on mispricing and include it into the FF-5 model to price IR and diversified the noise related to individual stocks. Behavioral stories for the low average returns of small stocks (IR puzzle) that invest a lot despite having low profitability face a serious challenge. IR is considered the mirror of investors' sentiments, investors' fear gauge (VIX), and many other risk measures that play a significant role between IR and cross-sectional returns of stocks (Bartram et al., 2009).

According to Fama and French (2015) that there are patterns relating to size, B/M, profitability, and investment in average returns. The FF-5 model aimed at capturing these trends that are rejected by the GRS test (Gibbons, Ross, & Shanken, 1989), but they documented that the model explains between 71% and 94% of the cross-section variance of expected returns for the portfolios of size, B/M, profitability and investment they examined. Value-weighted portfolios from univariate sorts on variables other than size are typically dominated by large stocks, and one of the main messages is that the asset pricing models have the most serious problems in small stocks that are high IR (Fama & French, 2015).

According to Yook (2010), undervalued stocks are either small firms or recent winners. To examine stock mispricing, the current study measures the relative mispricing of stocks by combining different firm-specific anomalies and new (additional) factors into one framework and constructs a modified factor of stock mispricing. The study follows the approach of Cao and Han (2016) to different aggregate anomalies to define relative mispricing. Under the costly arbitrage theory, this relation depends on whether the stocks are undervalued or overvalued.

In addition, Cao and Han (2016) documented that overvalued (small) stocks have low returns as compared to undervalued (large) stocks based on arbitrage score proxy by mispricing. They also documented that the arbitrage score strongly forecasts the cross-sectional expected returns; on average, high arbitrage score stocks outperform the others. Moreover, Stambaugh et al. (2015) also proved that cross-sectional returns are negative among overpriced but positive among underpriced stocks. Based on the arguments mentioned above, this study includes a new modified ranked mispricing arbitrage score factor into the FF-5 model to price IR into cross-sectional returns. This factor is included in the FF-5 model as mispricing modified 6th factor in order to price IR into cross-sectional returns. Following is the FF-5 equation by adding a new arbitrage score factor:

$$R_{i,m} = \alpha_i + \beta_{i,MRT}\,MRT_m + \beta_{i,SMB}SMB_m + \beta_{i,HML}HML_m + \beta_{i,RMW}RMW_m + \beta_{i,CMA}CMA_m + \beta_{i,AS}AS_{H-L,m} + \varepsilon_{i,m} \quad (3.14)$$

$AS_{H-L,m}$ is the modified mispricing arbitrage score high minus low factor calculated based on arbitrage score proxy for stock mispricing. $\varepsilon_{i,m}$ is the error term followed by $i.i.d$ assumption.

Following is the detailed procedure in order to measure the modified arbitrage score index. This study constructed an arbitrage score measure of relative stock mispricing based on a mixture of both quantitative and fundamental information. The arbitrage score proxy for stock mispricing is by considering aggregates four well-known anomalies and several new factors. The well-known anomalies include short-term return reversals, size, book-to-market, and momentum factor and new factors are investors fear gauge (VIX), downside beta, sentiment index, and downside co-skewness which have been ignored in the existing literature. Investor fear gauge as volatility of stock index (VIX) is calculated through the 360-day standard deviation of the return on the PSX-100 returns. In order to calculate the sentiment index, this study is used three firm-level proxies, viz. turnover, volatility premium, and equity share to measure the investor sentiment. The stock returns are volatile due to noise traders' error (Shefrin & Statman, 1995).

First, the volatility premium is the evaluation of the comparative value of extremely volatile stocks. It defines the moment when the risky stock valuation is low relative to the less risky stock valuation. It can also be interpreted as the measure of market-makers' response to more volatile stocks. Baker and Wurgler (2007) measured volatility by dividend premium and find that it can explain well the major historical trend in a firm's propensity to pay dividends. Another study by the same authors (Baker & Wurgler, 2006). They asserted that the relative premium on the dividend-paying stock is inversely related to investor sentiment. Volatility attracts day traders and the proportion of individual ownership increases in volatility. Volatile stocks are subject to noise trader, arbitrage, and fundamental risk. The volatility premium is defined as the natural log of the ratio of the value-weighted average market-to-book value of high volatile stocks to that of less volatile stocks.

The second one is the turnover. Turnover can be referred to as a measure of irrational exuberance. Higher liquidity indicates the overreaction of investors and as a result, overvaluation of stocks. Baker, Wurgler, and Yuan (2012) used turnover as a sentiment proxy and quantify it by taking the natural log of the ratio of volume and capitalization. And third and last proxy is equity share. It is the proportion of financing provided by the owners of a firm. This is a broader measure of equity financing that quantifies all equity instruments, not just IPOs. Equity share is defined as gross equity issuance divided by gross equity plus gross long-term debt issuance. All three coefficients of proxies are estimated by using the principal component approach and construct a sentiment index. Following is the detailed procedure for constructing the modified ranking mispricing factor.

1. At the beginning of each month, all stocks are independently sorted into a quantile basis from low to high, based on BE/ME (ratio of the book value of equity (BE) and market value of equity (ME).
2. Each stock is given the corresponding score of its quantile rank. The study defines the arbitrage score as the sum of all eight factors scores so that it ranges from 8 to 80.
3. Then, stocks with high arbitrage scores tend to be relatively undervalued stocks, while stocks with low arbitrage scores tend to be relatively overvalued stocks.

After constructing the high arbitrage and low arbitrage score portfolios, after take the difference of high-low arbitrage score make the factor named arbitrage score factor ($AS_{H-L,m}$) and include into the FF-5 model into pricing the mispricing proxies for IR.

3.6. Calculation of Tail Risk

In addition to IR puzzle, its determinants, and pricing, our sixth objective is to check the relationship of ITR with their returns and explore the ITR puzzle by considering only the tail distribution of overall sample countries and different groups of firms. To calculate the tail risk measure, we followed by Kelly and Jiang (2014). They present a particular method for calculating tail risk taking into account the rarity of tail data and the time-variant aspect of the tail index in stock return distributions. We employed this technique to calculate tail risk in the manner described below.

We first estimate the monthly tail risk series for every given stock market. For each month t, we pool all of the stocks' daily stock returns on trading days during that month into a whole sample in a given market, and estimate its tail index by using the method developed by Hill (1975).

$$\lambda_t^{Hill} = \frac{1}{K_t}\sum_{k=1}^{K_t} ln\frac{R_{k,,t}}{\mu_t} \tag{3.15}$$

where $R_{k,,t}$ is the k^{th} daily return that falls below an extreme value threshold μ_t during month t and K_t is the total number of such exceedances within month t. Following Kelly and Jiang (2014), we define μ_t as the fifth and first quantile of the cross-section in each period. After that we get two separate series one is extreme negative (fifth quantile) and second one is extreme positive (first quantile). Then we estimated the tail risk (denoted as TR_{KJ}) of firm i in month t for each equity market, based on the following model:

$$R_{i,t} = \mu_i + TR_{KJ,i,t}\ \lambda_t^{Hill} + \varepsilon_{i,t} \tag{3.16}$$

where $R_{i,t}$ is the monthly return of firm i in month t, and λ_t^{Hill} is the tail index as obtained from Equation (3.15). We adopted a rolling window with a length of 60 months to estimate $TR_{KJ,i,t}$ for stock i in month t.

After calculating the tail risk measure, the researcher followed the study of Long et al. (2018) to examine the ITR puzzle. The same procedure of Section 3.1.1.2 is followed to examine ITR puzzle by considering the following equation.

$$R_{i,m}^q = \delta_i^q + \delta_{i,\widehat{ITR}}^q \widehat{ITR}_m + \delta_{i,REV}^q REV_m + \delta_{i,Mom}^q Mom_m + \delta_{i,MB}^q MB_m + \delta_{i,DS\_CK}^q DS\_CK_m + \delta_{i,Beta}^q Beta_m + \varepsilon_{i,m}^q \tag{3.17}$$

where $\widehat{ITR}_{i,t}^q$ is ITR risk by considering only tail risk stocks and $\delta_{i,\widehat{ITR}}^q$ is the coefficient of tail risk.

3.7. Calculation of Jumps in Stock Prices

Our seventh objective is to examine the JR puzzle in the PSX and major equity markets of BRICS. Barndorff-Nielsen and Shephard (2006) used a bi-power variation (BPV) measure to separate the jump variance and diffusive variance. The current study is used their measure to detect jumps. They proposed the following processes for realized variance RV_t and realized bipower variation BV_t on day t.

$$RV_t = \sum_{i=1}^{M} (r_{t,i})^2 \rightarrow \int_{t-1}^{t} \sigma^2 ds + \sum_{i=1}^{M} (J_{t,i})^2 \tag{3.18}$$

$$BV_t = \frac{\pi}{2} \sum_{i=1}^{M} |r_{t,i}| \cdot |r_{t,i-1}| \rightarrow \int_{t-1}^{t} \sigma^2 \, ds \tag{3.19}$$

where $r_{t,i} = log\left({}^{s_{t,i}}/_{s_{t,t-1}}\right)$ is the i^{th} return on day t, and $s_{t,i}$ stock price. M is the sampling frequency, and σ^2 and $J_{t,i}$ are the diffusion and jump components of the stock price process, respectively. The difference between RV_t and $BV_{t,t}$ should be positive if there is a jump, and zero otherwise. This project adopts a ratio statistic RJ_t to determine if a jump occurs.

$$RJ_t = (RV_t - BV_t)/BV_t \tag{3.20}$$

The asymptotic variance of the ratio statistic is equal to

$s$where $TP_t$is defined as below

$$TP_t = M\mu_{\frac{4}{3}}^{-3} \sum_{t=1}^{M} |r_{t,i}|^{\frac{4}{3}} . |r_{t,i-1}|^{4/3} . |r_{t,i-2}|^{4/3} \tag{3.21}$$

with $\mu_k \equiv \frac{2^{k/2}\tau\left(\frac{(k+1)}{2}\right)}{\tau(1/2)}$.

According to the simulation analyses ,the ratio $z = {}^{RJ_t}/_{Avar(RJ_t)}$ converges to the standard normal distribution. Once it has been confirmed whether or not a jump occurred on day t, following the daily realized jumps (J_t) can be filtered out:

$$J_t = sign(r_t).\sqrt{RV_t - BV_t}.I(z > \emptyset_{\alpha}^{-1}) \tag{3.22}$$

Here, $\emptyset$ is the standard normal c.d.f. and α is the level of significance chosen at 0.999. The moments of the jump distribution J_t, such as its numerical mean and standard deviation, can be directly estimated. For each stock, this paper uses the sum of J_t, over all trading days of a month as the monthly measurement of realized jumps. This paper also uses an alternative level of significance at 0.990 to classify days with jumps, and this consequently leads to a much higher portion of jump days where the monthly frequency of the jump variable has the tendency to be truncated towards 1.

After the calculation of the JR series, examine the JR puzzle by following the same procedure in Section 3.1.3.4. The following equation will be estimated to check the JR puzzle.

$$R_{i,m}^{q} = \delta_{i}^{q} + \delta_{i,\widehat{JR}}^{q}\widehat{JR}_{m} + \delta_{i,REV}^{q}REV_{m} + \delta_{i,Mom}^{q}Mom_{m} + \delta_{i,MB}^{q}MB_{m} + \delta_{i,DS\_CK}^{q}DS\_CK_{m} + \delta_{i,Beta}^{q}Beta_{m} + \varepsilon_{i,m}^{q} \tag{3.23}$$

where, $\widehat{JR}_{m}$ is the jump risk by considering only those stocks that contain large discontinuous changes in their prices and $\delta_{i,\widehat{JR}}^{q}$ is the coefficient of the JR variable.

3.8. Measurement Procedure for Different Categories of Firm

In order to achieve the second and eighth objectives, firms are divided into different groups such as small, medium, and large beta-based firms, liquid, and illiquid firms, financially constrained and unconstrained firms. (Jing, Chen, & Cai, 2012; Kaplan & Zingales, 1997; Ke et al., 2014; Zingales, 2008). In order to capture the differences and similarities among these groups of firms, it is, therefore, questionable to consider and examine IR, jump, and tail risk puzzles in separate groups of firms.

The current study categorizes firms by following characteristics to test the relationship between cross-sectional returns and IR. Firms' stock return volatility varies across firms' distinct characteristics, and the factors driving the volatility can contribute both positively and negatively to the economic growth of capital markets So, it is likely that the firm's specific risk varies among different types of firms having distinct characteristics. The problem can be even more severe for operating companies where liquidation of assets in these companies is limited to the amount of debt the company has. The vulnerability to past stock returns must be higher for new, young, unseasoned stocks as compared to the older and mature stocks having a high reputation in performance.

Consequently, in the long run, mature stocks can earn high returns since more funds are available in order to get arbitrage opportunities. In contrast, new arbitrageurs lose their funds precisely when the potential returns are the highest, and hence, their average returns are lower than those of the older stocks. Based on this, the current study also examines the behavior of IR, tail, and JR by firms dividing into different groups such as large, small and medium-beta firms, and financially constrained and unconstrained firms and more liquid and less liquid firms. The following are the brief measurement and description of these firms' categories.

3.8.1. Beta-Based Firms

We estimate the following regression by applying the rolling window technique to get a dynamic series of betas.

$$R_{i,d} - R_f = \alpha_i + \beta_{i,MRT} (MRT_d - R_f) + \varepsilon_{i,d} \quad (3.24)$$

where $R_{i,d}$ is the excess daily returns of firm i. MRT_d is the daily excess market return. $\beta_{i,MRT}$ is the required value of the beta series. After estimating the time-varying betas series, we divided the firms into high-, low-, and medium-beta firms. For instance, percentile 25th and 75th percentile are considered low, and high beta between these are included in medium beta firms.

3.8.2. Liquid and Illiquid Firms

Stock liquidity is the ratio of the absolute daily return to the trading volume on that day. The study uses the measure of illiquidity proposed by Amihud (2002), to divide the firms based on liquidity. It is calculated as:

$$ILLIQ_{i,t} = |R_{i,t}|/VOL_{i,t} \tag{3.25}$$

$R_{i,t}$ is the return on stock i at time t and $VOL_{i,t}$ is the respective daily volume. This ratio gives the absolute (percentage) price change of the daily trading volume or the daily price impact of the order flow. Based on the median value of illiquidity, we divided the firms into low illiquid (liquid) and high illiquid firms.

3.8.3. Financially Constrained and Unconstrained Firms

The third classification of firms is based on financially constrained (FC) and unconstrained (FUC). The endogenous switching regression model (Lokshin & Sajaia, 2004) identifies FC and FUC. The following regression equations are used to determine the regime of FC and FUC.

$$\left(\frac{I_{i,t}}{K_{i,t-1}}\right)^{FC} = X_{i,t}\varphi_1 + \vartheta_{1,i,t} \qquad if \ W_{i,t}\gamma + \varepsilon_{i,t} \geq 0 \tag{3.26.1}$$

$$\left(\frac{I_{i,t}}{K_{i,t-1}}\right)^{FUC} = X_{i,t}\varphi_2 + \vartheta_{2,i,t} \qquad if \ W_{i,t}\gamma + \varepsilon_{i,t} < 0 \tag{3.26.2}$$

where $X_{i,t}$ vector shows the determinants of corporate investments. $\varphi_1, \varphi_2,$ and γ are the vector of parameters to be estimated. $\vartheta_{1,i,t}, \vartheta_{2,i,t}, and\ \varepsilon_{i,t}$ are respective error terms that are supposed to be correlated across equations, but not over time, and are vectors of parameters to be estimated, while respective error terms are supposed to be correlated across equations, but not overtime. Table 1 presents the definition of the variables in investment and selection equations. The first part of equations (3.26.1) and (3.26.2) constitutes the structural equations showing investment behaviour in financially constraints and unconstraints regimes, respectively. The second (conditional) part of equations (3.26.1) and (3.26.2) represents the switching function that is estimated simultaneously with the investment equations. The sample separation is, therefore, unknown but comes from the process given by the above expressions. Once the equations are simultaneously estimated, the respective probabilities of the firm being in either regime are calculated. Following is the structural equation:

$$\frac{I_{i,t}}{K_{i,t-1}} = \rho \frac{I_{i,t-1}}{K_{i,t-2}} + \gamma_0 \Delta y_{i,t} + \gamma_1 \Delta y_{i,t} + \theta\left(k_{i,t-2} - y_{i,t-2}\right) + \pi_0 \frac{CF_{i,t}}{K_{i,t-1}} + \pi_1 \frac{CF_{i,t-1}}{K_{i,t-2}} + d_t + \mu_i + \vartheta_{i,t} \tag{3.27}$$

where $K_{i,t-1}$ is a model parameter. $I_{i,t}$ denotes gross investment of firm i at time t. $K_{i,t-1}$ denotes capital stock at the beginning of the period. $y_{i,t}$ is a log of sales. $\frac{CF_{i,t}}{K_{i,t-1}}, \frac{CF_{i,t-1}}{K_{i,t-2}}$ are the current and lagged value of a firm's cash flow normalized by $K_{i,t-1}$ and $K_{i,t-2}$, respectively. By estimating a Heckman-type panel probit model, we calculate the probability (less than 50% is considered as financially constrained firms and greater than 50% is considered financially constrained firms) that the firm is in a financially constrained regime based on determinant $X_{i,t}$. d_t is a time dummy variable.μ_i is an unobserved firm-specific effect and $\vartheta_{i,t}$ is an error term. $\rho, \gamma_0, \gamma_1, \theta, \pi_0, and\ \pi_1$ are the model parameters.

Table 3.1: Variable Definition

$X_{i,t}$ contains the following first four factors that determine the propensity of a firm to be in one regime (FC) or the other (FUC)	
Firm Size	The logarithm of total sales of a firm
$EBITD/_{Debt}$	The ratio of earnings before interest, taxes, and depreciation to total debt
Financial Slack	(Cash holding plus short-term investment)/total asset
Interest Coverage Ratio	Interest expenses/EBITD
Investment	Capital expenditure/total asset
Firm' Output	Log of firms' sales
Firm Cash Flows	The current and lagged value of the firm's cash flow normalized by $K_{i,t-1}$ and $K_{i,t-2}$, respectively.
Firm Age	The log of the number of years a company has been in operations.
Time Dummy	It is a time dummy variable.

3.9. Idiosyncratic Risk and Idiosyncratic Tail Risk over Time

In addition, we examine the trend or behaviour of IR and ITR over time. Firm-specific risk can be examined in different ways, but it often involves tracking the risk over some sample period and capturing the trends or behavior of the risk over time. The biggest challenge in firm-specific risk is the speed with which it can change. Sometimes it surges rapidly, and the magnitude can be very large. As a result, the risks of assets and portfolios can change significantly, even when the underlying holdings are static. Said differently, firm-specific risk changes a great deal over time. Sometimes this change is slow; other times, it can be very rapid and subject to jumps. This can induce enormous changes in portfolio risk. The literature has provided several explanations for variation in these risks, and they can be broadly classified based on macroeconomic variables, for instance, market risk (Chen & Petkova, 2012) or firm characteristics, for example, small and young firms, high leverage, low profitability, and less liquid firms.

The current study examines whether these risks follow some trends over time. If yes, then whether these have increasing or decreasing trends. More specifically, the current study observed IR and ITR tendencies in the stock market crash periods. For this, these risks are presented through graphs over the considered period and examined the trends, more specifically, in the stock market crash periods.

Chapter 4

Results and Discussion

4.1. Introduction

This chapter examines the IR puzzle based on a preliminary portfolio-level analysis. Next, we formally look at the IR puzzle's presence using a parametric test called a t-test, capital asset pricing models, a nonparametric test of stochastic dominance, and quantile regressions of all manufacturing firms listed on the BRICS' and Pakistan stock markets. After presenting evidence on the IR puzzle in the full sample, the puzzle is also examined in different groups based on fundamental characteristics, such as market risk, financially constraints, and liquidity position. After that, the determinants of IR for all sample firms and different groups of firms are found for considered sample countries. Finally, we present the results after adding a modified mispricing arbitrage score factor to the asset pricing models to check whether the IR is appropriately priced in the stock market.

Next, we examine the ITR and JR puzzles for all firms and in different groups of firms. After that, we look the pattern of IR and ITR graphically to check whether these risks have increasing or decreasing trends. Following are the results, along with the details interpretations.

4.2. Descriptive Statistics

Table 4.1 shows the summary statistics of monthly stock returns and other important variables of Pakistan and BRICS member countries. For Pakistan, Brazil, Russia, and South Africa, the monthly average returns are negative, along with high values of standard deviations. Moreover, the magnitude of monthly returns varies dramatically across countries. Among BRICS member countries, the lowest monthly returns are -0.0819% for Russia, and the highest returns are 0.3437% for India. Similarly, the highest IR value among BRICS member countries is 0.3191 for India, and the lowest value is 0.0249 for Brazil. We also report the monthly returns for developing countries like Pakistan. The monthly return is -0.1112% for Pakistan, with the highest IR value of 0.9763 among all considered sample countries.

The usual distribution measures, such as skewness and excess kurtosis of stock returns, show that the return distributions of the sample countries are non-normal and negatively skewed, and leptokurtic distribution behavior on average is observed. After that, when we look at the core risk measure values of IR, downsize co-skewness and downsize beta, these are primarily negative and are found appropriate for emerging markets where mean return distributions are negative (Galagedera & Brooks, 2007).

The average value of downsize co-skewness and down-size beta is negative, and its minimum values appear to suffer highly negative ones. Down-size beta shows value implies the stocks' fluctuations against changes in the stock market, especially when the stock market is going down. The average log of total asset value is reported as firm size, and values of fit size are large, having double digits. The study uses the illiquidity measure (absolute stock returns divided by volume) to measure the firm's liquidity. The mean value implies that all equity firms are pretty leveraged. The stock returns of the previous months, called return reversal, also show positive values for Russia and China only. Further, momentum return is positive only for Russia, which exhibits the difference between loser and winner portfolio returns.

Table 4.1: Summary Statistics

			Pakistan			
Variables	**Mean**	**Std.**	**Minimum**	**Maximum**	**Skewness**	**Excess Kurtosis**
Monthly Returns	-0.1112	1.4968	-13.2176	13.8995	2.5468	19.1810
Idiosyncratic Risk	0.9763	0.9560	0.0001	8.2888	1.9162	7.0543
Down Size Co-Skewness	-3.4353	5.9061	-45.0289	-.53765	-4.7329	28.4796
Down Size Beta	-0.2324	0 .5028	-8.3163	-4.3400	-7.3213	83.8522
Firm Size	14.8348	1.7208	8.7015	20.4619	0 .2140	3.1595
Liquidity	0.0115	.11823	0000	5.7621	18.9706	505.3146
Return Reversal	-0.1089	2.0386	-17.0343	15.7351	-0.0894	15.0238
Momentum Return	-0.4952	9.3866	-113.6822	29.71463	-1.1448	8.7438
			Brazil			
Variables	**Mean**	**Std.**	**Minimum**	**Maximum**	**Skewness**	**Excess Kurtosis**
Monthly Returns	-0.0653	0.0123	-1.3114	0.4956	-39.2759	33.5390
Idiosyncratic Risk	0.0249	0.0289	0000	1.0035	7.0479	11.1746
Down Size Co-Skewness	-.0835	0.0300	-.35792	-0.0219	-9.4576	105.306
Down Size Beta	5.4919	2.8725	1.000	10.000	0.0017	1.7754
Firm Size	14.4358	2.1248	3.1780	20.5789	-0.8996	5.8158
Liquidity	0.0302	0.03996	0.4116	2.9815	47.8860	314.6720
Return Reversal	-0.0642	0.0458	-9.1800	4.5974	-37.1296	646.974
Momentum Return	-0.0107	0.0410	-1.7562	0.5101	-10.6763	242.178
			Russia			
Variables	**Mean**	**Std.**	**Minimum**	**Maximum**	**Skewness**	**Excess Kurtosis**
Monthly Returns	-0.0819	0.0172	-1.5447	0.6274	-37.3748	3250.002
Idiosyncratic Risk	0.0308	.05477	0.0001	4.0869	28.58348	1579.274
Down Size Co-Skewness	-.03657	.08490	-1.4886	-0.0109	-9.71381	148.2046
Down Size Beta	-25.585	45.291	-38.0129	-0.0222	-56.2297	42.5397
Firm Size	17.2693	2.3518	6.4846	24.1624	.04436	2.9837
Liquidity	0.06142	0.0181	0000	2.3359	96.9686	11.4714
Return Reversal	0.04391	.05854	-3.4609	4.22291	16.5937	22.4965
Momentum Return	0.0110	0.0892	-2.5206	2.9976	1.03313	149.344
			India			
Variables	**Mean**	**Std.**	**Minimum**	**Maximum**	**Skewness**	**Excess Kurtosis**
Monthly Returns	0.3437	0.1395	-0.3534	6.738	20.394	116.83
Idiosyncratic Risk	0.3191	0.474	0.0003	3.312	50.310	325.05
Down Size Co-Skewness	-0.2375	0.5128	-3.0897	-0.0159	-3.9255	19.006

Down Size Beta	-0.0866	0.1037	-0.44317	-0.0003	-1.4257	4.3963
Firm Size	16.6217	1.94311	10.3182	22.610	0.2161	2.8918
Liquidity	0.00661	0.0024	0000	0.14343	48.932	260.377
Return Reversal	-0.0124	0.0437	-0.4634	2.2594	24.444	127.631
Momentum Return	-0.0036	0.1097	-3.6235	0.4113	-17.2702	426.972

China

Variables	Mean	Std.	Minimum	Maximum	Skewness	Excess Kurtosis
Monthly Returns	0.0189	0.0188	-0.3565	0.1976	-3.5968	73.4501
Idiosyncratic Risk	0.0275	0.0290	0000	1.8822	35.5350	17.2837
Down Size Co-Skewness	-0.0127	0.0143	-0.5692	-0.0001	-19.7876	15.34
Down Size Beta	3.1679	1.1842	1.000	7.0908	0.00275	4.8354
Firm Size	15.1242	1.4846	9.7865	21.6023	0.67346	3.7522
Liquidity	0.00297	0.00127	0000	0.08558	53.6428	30.6851
Return Reversal	0.0197	0.0256	-0.2252	0.3651	0.33279	8.4664
Momentum Return	-0.0109	0.0290	-0.4238	0.3283	-2.10725	31.7920

South Africa

Variables	Mean	Std.	Minimum	Maximum	Skewness	Excess Kurtosis
Monthly Returns	-0.0182	0.0873	-6.0255	6.7334	3.6053	1490.002
Idiosyncratic Risk	0.0342	.08347	0.0001	2.1703	14.301	277.6389
Down Size Co-Skewness	-0.0559	0.0488	-0.0252	-0.0034	-22.3622	716.3556
Down Size Beta	-8.4260	63.625	-37.38	-0.0001	-31.0286	147.5377
Firm Size	14.5477	2.3140	4.3820	26.7467	-0.3904	3.43631
Liquidity	0.0367	0.7930	0000	0.67334	29.7193	214.266
Return Reversal	-0.0178	0.0867	-6.0222	6.7334	3.59354	148.0993
Momentum Return	-0.0263	0.2476	-4.9203	1.16073	-1.17090	12.19984

Note: Table shows the descriptive statistics of monthly stock returns and the core variables of emerging and Pakistan stock exchange.

4.3. Correlation Analysis

Table 4.2 provides the results of the cross-sectional correlation between IR and other key variables. In addition, this table reported the results of paired sample student *t*-test to test whether the difference between IR and stock returns is statistically different from zero. The Pearson correlation coefficient values are reported in the second column of the table. The correlation values of the first variable monthly returns with IR are negative and highly significant for all sample countries. It implies a negative relation, which contradicts the CAPM theory. This negative relationship between IR and stock returns indicates the IR puzzle (Ang et al., 2006). These findings support our hypothesis that firms with high IR have subsequent low returns. Further, the correlation coefficient of the considered variables with IR is statistically significant.

The third column of the table shows the *t*-test values. The t-statistics show that the difference between IR and monthly returns is economically significant at all conventional levels. Similarly, there is an effective and statistically positive mean difference of IR with all considered variables except for firm size in China and down beta in South Africa. Higher triple-digit t-values show a considerable difference between the paired samples.

Table 4.2: Cross-sectional Correlation with Idiosyncratic Risk and *t* Statistics

Variables	Correlations	P-values	Newey-West *t* statistics
Pakistan			
Monthly Returns	-0.0799***	0.000	129.741
Down Size Co-Skewness	0.0023*	0.674	133.9293
Down Size Beta	0.1162***	0.000	110.7343
Firm Size	-0.1114***	0.000	-0.0031
Momentum Return	0.0143***	0.007	27.9742
Illiquidity	0.0342***	0.000	208.7646
Return Reversal	-0.0404***	0.000	102.2892
Brazil			
Monthly Returns	-0.0889****	0.000	67.826
Down Size Co-Skewness	0.0033*	0.067	44.450
Down Size Beta	-0.0840***	0.000	37.7889

Firm Size	-0.0926**	0.000	5.0042
Momentum Return	-0.0246***	0.007	40.8139
Illiquidity	0.0687***	0.000	32.868
Return Reversal	0.0165***	0.000	42.3937
Russia			
Monthly Returns	-0.3817*	0.000	81.067
Down Size Co-Skewness	0.3609*	0.074	60.697
Down Size Beta	0.0159*	0.080	6.232
Firm Size	-0.1414***	0.000	1.235
Momentum Return	0.0001	0.983	51.183
Illiquidity	0.2361***	0.000	110.30
Return Reversal	0.0930***	0.000	66.822
India			
Monthly Returns	-0.1166***	0.000	49.47
Down Size Co-Skewness	-0.0427	0.674	22.516
Down Size Beta	-0.2591***	0.000	18.132
Firm Size	-0.2822***	0.000	57.920
Momentum Return	-0.0128	0.3384	22.129
Illiquidity	0.1186***	0.000	99.928
Return Reversal	0.5900***	0.000	58.014
China			
Monthly Returns	-0.0655***	0.000	17.822
Down Size Co-Skewness	0.0563*	0.057	14.1450
Down Size Beta	0.01780***	0.000	17.1790
Firm Size	-0.0559***	0.000	15.1842
Momentum Return	-0.0225**	0.033	10.009
Illiquidity	0.0143*	0.0928	12.0268
Return Reversal	0.0665***	0.000	12.1937
South Africa			
Monthly Returns	-0.0778***	0.001	31.6029
Down Size Co-Skewness	0.0090***	0.004	59.546
Down Size Beta	0.0181***	0.001	-5.803
Firm Size	-0.2230***	0.000	21.2327
Momentum Return	-0.0237***	0.003	49.2686
Illiquidity	0.2477***	0.000	12.030
Return Reversal	-0.0281***	0.000	11.1491

Note: The table shows the correlation between idiosyncratic risk with core variables and their p-value along with the Newey-West *t* statistics. ***, **, * shows the significance level for 1%, 5%, and 10% respectively.

By looking at it briefly, we can see evidence of the statistically significant correlation between IR and the core variables and the signs according to the proposed hypothesis. For instance, monthly returns negatively correlate with the IR throughout the sample countries. Similarly, firm size and IR are negatively correlated for all sample countries. Firm illiquidity has a statistically positive relationship with IR. Understanding such relation through Pearson correlation values is useful because we can use the value of one variable to predict as the determinant of IR. Said differently, through these preliminary results, we can find the determinants of IR through formal regression analysis.

4.3. Idiosyncratic Risk Puzzle: Portfolio-Level Analysis

In this section, we examine the IR puzzle through portfolio analysis. We first conduct a portfolio-level analysis to explore the values of the IR portfolios on stock returns. Based on IR and size portfolios, we sort firms into five quintiles each month. The result shows that the IR is negatively and significantly related to the expected returns in our sample based on size and IR portfolios. Table 4.3 reports the results of equal-weighted and value-weighted returns for Pakistan and BRICS countries. The preliminary evidence supports our hypothesis that the IR's contemporary returns on stocks in the fifth quintile are significantly lower than those in the first quintile. Similarly, the smallest portfolios have low returns. This implies that small firms have high IR (FU, 2010).

In other words, in equal-weighted portfolios of IR, the average returns tend to be larger in low IR than in the high-IR portfolios for each sample country, and the difference between the highest and the lowest IR portfolios is nonzero and statistically significant at conventional levels based on the *t*-test results. Specifically, the largest statistical difference is observed for India. These results demonstrate patterns similar to those Ang et al. (2006) reported. According to their research, firms with high IR have low returns. These results show that the IR puzzle is robust, includes the financial crisis period, and uses a more extended period to estimate IR. The second objective of this section is to check whether the preliminary evidence supports the IR puzzle by showing the performance of stock returns in size portfolios. The size portfolio shows that, on average, Size 5 has higher returns than its extreme counterpart portfolios. The mean difference test values also significantly differ among the extreme-sized portfolios. In other words, Table 4.3 further confirms that firms with high IR are small in size. Thus, preliminary results indicate the existence of the IR puzzle in Pakistan and BRICS countries. This negative relationship between IR and size is not surprising due to the negative correlation between the two variables found in previous studies (H Décaire, 2021; Liu & Wang, 2021).

Table 4.3: Stock Returns of Size and Idiosyncratic Risk sorted Portfolios

	Pakistan		
Idiosyncratic Risk Portfolios	**Equal Weighted Returns**	**Size Portfolios**	**Value Weighted Returns**
IR1 (Low)	-0.1386	Size1 (Small)	-0.3139
IR2	0.0991	Size2	-0.1955
IR3	0.1465	Size3	-0.0322
IR4	0 .0105	Size4	0.0196
IR5 (High)	-0.6543	Size5 (Large)	0.1381
IR5-IR1	-0.5157	Size5- Size1	0.4520
t statistic	-26.3255	t statistic	20.8745
p-values	0.000	p-values	0.000

	Brazil		
Idiosyncratic Risk Portfolios	**Equal Weighted Returns**	**Size Portfolios**	**Value Weighted Returns**
IR1 (Low)	0.6790	Size1 (Small)	-0.0439
IR2	0.2663	Size2	-0.0436
IR3	0.9430	Size3	-0.0108
IR4	-0.0189	Size4	0.0875
IR5 (High)	-0.0127	Size5 (Large)	0.0261
IR5-IR1	-0.6917	Size5- Size1	-0.0178
t statistic	1.5306	t statistic	12.6864
p-value	0.0629	p-value	0.000

	Russia		
Idiosyncratic Risk Portfolios	**Equal Weighted Returns**	**Size Portfolios**	**Value Weighted Returns**
IR1 (Low)	0.0971	Size1 (Small)	-0.0811
IR2	-0.2486	Size2	0.0699
IR3	-0.665	Size3	-0.0202
IR4	-0.1535	Size4	-0.0339
IR5 (High)	-0.3815	Size5 (Large)	0.02827
IR5-IR1	-0.4786	Size5- Size1	0.1093
t statistic	3.2681	t statistic	1.6165

p-value	0.090	p-value	0.053

Table 4.4: Idiosyncratic Risk Puzzle in Full Sample Firms

India

Idiosyncratic Risk Portfolios	**Equal Weighted Returns**	**Size Portfolios**	**Value Weighted Returns**
IR1 (Low)	0.0852	Size1 (Small)	-0.0142
IR2	0.0899	Size2	0.02404
IR3	0.0105	Size3	0.03201
IR4	0.04422	Size4	0.04933
IR5 (High)	-0.05314	Size5 (Large)	0.04028
IR5-IR1	-0.03206	Size5- Size1	0.05448
t statistic	-5.4474	t statistic	9.6682
p-value	0.000	p-value	0.000

China

Idiosyncratic Risk Portfolios	**Equal Weighted Returns**	**Size Portfolios**	**Value Weighted Returns**
IR1 (Low)	0.06136	Size1 (Small)	-0.02968
IR2	0.05287	Size2	0.01149
IR3	-0.01837	Size3	0.01049
IR4	-0.03893	Size4	0.01325
IR5 (High)	-0.02871	Size5 (Large)	0.01428
IR5-IR1	-0.09007	Size5- Size1	-0.0154
t statistic	6.9394	t statistic	7.5466
p-values	0.000	p-values	0.000

South Africa

Idiosyncratic Risk Portfolios	**Equal Weighted Returns**	**Size Portfolios**	**Value Weighted Returns (Mean Difference Value)**
IR1 (Low)	0.02096	Size1 (Small)	-0.01327
IR2	0.04807	Size2	-0.02416
IR3	0.05124	Size3	0.01158
IR4	0.00610	Size4	0.03464
IR5 (High)	-0.08530	Size5 (Large)	0.11530
IR5-IR1	-0.10626	Size5- Size1	0.12857
t statistic	3.3481	t statistic	6.8965
p-value	0.090	p-value	0.053

Note: Idiosyncratic equal-weighted and sized-based value-weighted portfolios are constructed to check the existence of the IR puzzle and applied *t*-test for Pakistan and BRICS countries.

4.4. Idiosyncratic Risk Puzzle: Asset Pricing Models

Table 4.4 shows the IR puzzle in the asset pricing context. We applied the one-factor, three-factor, and five-factor Fama-French CAPM and Carhart model to each quintile portfolio of

Models	IR1	IR2	IR3	IR4	IR5	IR5-IR1
			Pakistan			
One-Factor	0.3394**	0.3308**	0.3022**	0.3081**	0.3226**	-0.0168
CAPM	(0.115)	(0.116)	(0.115)	(0.116)	(0.177)	(4.928)
Three-Factor	-0.3570***	-0.3615***	-0.3599***	-0.3545***	-0.3599***	-0.7169
CAPM	(0.814)	(0.714)	(0.874)	(0.135)	(0.245)	(11.028)
Four-Factor	-2.7438**	-2.7667**	-2.7620**	-2.7550**	-2.7981***	-0.0543
Carhart	(0.235)	(0.256)	(0.258)	(0.269)	(0.279)	(7.197)
Four-Factor	-1.7635**	-1.7683**	-1.7579**	-1.7561**	-1.7697**	-0.0062
CAPM	(0.271)	(0.291)	(0.298)	(0.308)	(0.329)	(8.183)
Five-Factor	-1.1184**	-1.1440**	-1.1447**	-1.1507**	-1.2106**	-0.0092
CAPM	(0.273)	(0.291)	(0.301)	(0.319)	(0.329)	(0.393)
			Brazil			
One-Factor	-0.962***	-0.946***	-0.961***	-0.963***	-0.965***	-1.927
CAPM	(0.0501)	(0.0487)	(0.0465)	(0.0476)	(0.0497)	(79.220)
Three-Factor	-0.920***	-0.922***	-0.925***	-0.927***	-0.937***	-0.0017
CAPM	(0.0502)	(0.0481)	(0.0467)	(0.0480)	(0.0503)	(153.890)
Four-Factor	0.748***	0.631***	0.675***	0.698***	0.653***	-0.0095
Carhart	(0.0384)	(0.0388)	(0.0387)	(0.0389)	(0.0392)	(9.548)
Four-Factor	-0.808***	-0.803***	-0.813***	-0.813***	-0.812***	-0.0004
CAPM	(0.0553)	(0.0529)	(0.0526)	(0.0537)	(0.0056)	(23.543)
Five-Factor	-0.807***	-0.802***	-0.812***	-0.810***	-0.811***	-0.0004
CAPM	(0.0561)	(0.0537)	(0.0535)	(0.0547)	(0.0057)	(6.487)
			Russia			
One-Factor	-0.0123	-0.0102***	-0.0150*	-0.0106*	-0.0133	-0.001
CAPM	(0.0235)	(0.0231)	(0.0236)	(0.0024)	(0.0243)	(56.874)
Three-Factor	-0.0336	-0.0130***	-0.0181**	-0.0188*	-0.0193***	-0.0529
CAPM	(0.0249)	(0.0248)	(0.0253)	(0.0255)	(0.0026)	(34.975)
Four-Factor	0.0190***	0.0184***	0.0163	0.0162	0.0174	-0.0016
Carhart	(0.0919)	(0.0095)	(0.0972)	(0.0954)	(0.0947)	(58.574)
Four-Factor	0.0428***	0.0339***	0.0309***	0.0405***	0.0416***	-0.0012
CAPM	(0.0207)	(0.0021)	(0.0214)	(0.0213)	(0.0215)	(11.457)
Five-Factor	0.0423***	0.0331***	0.0302***	0.0398***	0.0416***	-0.0007
CAPM	(0.0206)	(0.0209)	(0.0214)	(0.0212)	(0.0214)	(56.984)
			India			
One-Factor	-0.536***	-0.532***	-0.531***	-0.535***	-0.538***	-0.0020
CAPM	(0.0063)	(0.0598)	(0.0616)	(0.0592)	(0.0637)	(78.342)
Three-Factor	-0.503***	-0.502***	-0.494***	-0.500***	-0.504***	-0.001
CAPM	(0.0491)	(0.0472)	(0.0468)	(0.0473)	(0.0508)	(11.754)
Four-Factor	0.164**	0.153	0.159*	0.0940*	0.0113*	-0.1527
Carhart	(0.0538)	(0.0590)	(0.057)	(0.0577)	(0.0665)	(45.987)
Four-Factor	-0.507***	-0.502***	-0.496***	-0.503***	-0.508***	-0.001
CAPM	(0.0482)	(0.0464)	(0.0462)	(0.0469)	(0.0504)	(47.986)
Five-Factor	-0.474***	-0.472***	-0.472***	-0.475***	-0.479***	-0.005
CAPM	(0.0456)	(0.0437)	(0.0440)	(0.0443)	(0.0494)	(45.987)
			China			
One-Factor	-0.0342***	-0.0306***	-0.0454***	-0.0456***	-0.0462***	-0.0120
CAPM	(0.0317)	(0.0321)	(0.0321)	(0.0321)	(0.0309)	(5.765)
Three-Factor	-0.0434***	-0.0496 ***	-0.0526***	-0.0518***	-0.0538***	-0.0104
CAPM	(0.0396)	(0.0321)	(0.0317)	(0.0319)	(0.0309)	(7.980)
Four-Factor	-0.0493	-0.0380	-0.0109	-0.0371	-0.0708	-0.0215
Carhart	(0.0595)	(0.0596)	(0.0614)	(0.0601)	(0.0580)	(4.675)
Four-Factor	-0.0426***	-0.0476***	-0.0533***	-0.0505***	-0.0506***	-0.0080
CAPM	(0.0311)	(0.0315)	(0.0316)	(0.0314)	(0.0306)	(8.957)

Five-Factor CAPM	-0.0876*** (0.033)	-0.0828*** (0.033)	-0.0990*** (0.0329)	-0.0958*** (0.0335)	-0.0997*** (0.0033)	-0.0121 (5.897)
			South Africa			
One-Factor CAPM	0.0172*** (0.0140)	0.0171*** (0.0130)	0.0160*** (0.0136)	0.0158*** (0.0140)	0.0151*** (0.0139)	-0.0021 (12.564)
Three-Factor CAPM	0.0135*** (0.0134)	0.0133*** (0.0135)	0.0130*** (0.0133)	0.0114*** (0.0136)	0.0118*** (0.0139)	-0.0017 (11.785)
Four-Factor Carhart	-0.0915*** (0.0199)	-0.0834*** (0.0194)	-0.0870*** (0.0195)	-0.9060* (0.0198)	-0.1106*** (0.0197)	0.0804 (14.869)
Four-Factor CAPM	0.0127*** (0.0136)	0.0125*** (0.0134)	0.0123 *** (0.0138)	0.0109 *** (0.0135)	0.0113*** (0.0137)	-0.0014 (13.876)
Five-Factor CAPM	0.0127*** (0.0146)	0.0122*** (0.0147)	0.0123*** (0.0144)	0.0122*** (0.0146)	0.0123*** (0.0143)	-0.004 (11.786)

Note: The table presents the IR puzzle results based on quintile IR portfolios for all manufacturing firms of Pakistan and BRICS countries. Alpha is estimated using one factor to five factors CAPM models and presented along with their standard errors below in parentheses. ***, **, * shows the level of significance for 1%, 5%, and 10% respectively.

IR for each country separately. The table shows the estimated alpha values and their standard deviations in parentheses. We also added the column IR5-IR1 for comparison purposes, which shows the difference in alpha values between IR5 and IR1, and *t* statistics are presented using the mean-variance efficiency test that states the null hypothesis that the intercepts are all zero (Gibbons et al., 1989). We estimate the one-factor, three-factor, four-factor, and five-factor CAPM models by considering the portfolio returns as a dependent variable and reporting their standard errors. As hypothesized, the IR is higher from the IR1 portfolio to the IR5 portfolio. The spread in IR5-IR1 shows a statistically significant difference between the highest and lowest IR portfolios, pervasive across emerging economies. These findings are for the one- to five-factor CAPM and Carhart models. Based on the estimated alpha in the asset pricing models, we find comparable and noteworthy findings that reveal the IR puzzle in all the emerging countries of BRICS and the developing country of Pakistan.

The performance of each portfolio is shown through the alpha values derived from CAPM models, and higher alpha values indicate more significant returns than predicted. To put it another way, the positive alpha value implies that the portfolio managers outperformed the risk-reward that they expected of the fund. A negative alpha indicates that the management performed worse than it should have, given the portfolio's required return (Phuoc, 2018). However, the absolute alpha values matter, as they show abnormal performance or returns. The strength and patterns of these alpha values can differ from country to country. For example, we can see a clear systemically declining pattern in Brazil and South Africa. That is, average portfolio returns decrease as the IR increases throughout CAPM's one to five factors.

Furthermore, the difference in average returns between the portfolios with the highest and lowest IR is negative and significant at the 1 percent level. The results for Russia, India, and China show negative alpha values that, in some places, decrease monotonically from the lowest IR to the highest IR quintile portfolios. The difference in the alpha values among the one- to five-factor CAPMs is statistically significant, at least at the 5 percent level. However, the results of the Carhart model are somewhat mixed. For instance, there is a weak indication in Russia of the IR puzzle only for the first and second quintiles of IR. Although the remaining alpha values show a declining trend, they are not statistically significant. Similarly, the alpha values estimated with the Carhart model show a weak indication of the IR puzzle in India. No evidence of the IR puzzle is found in China.

Overall, the results reveal a significantly negative relationship between IR and stock returns in all sample emerging markets and developing country Pakistan. The GRS *t* statistics show that the estimated alpha values are nonzero and statistically significant. A systemic pattern of alpha values is observed in the lowest to the highest IR portfolios. Thus, this dilemma is referred to as the "IR puzzle."

4.5. Idiosyncratic Risk Puzzle: Non-Parametric Approach

After performing the parametric technique (t-test and asset pricing models), we employ the nonparametric approach, such as stochastic dominance (SD) and quantile regression, to examine the IR puzzle. Following are the detailed results of these non-parametric techniques.

4.5.1. Idiosyncratic Risk Puzzle: Stochastic Dominance Approach

We perform the KS test (Barrett & Donald, 2003) by applying the first-, second-, and third-order SD (hereafter, SD1, SD2, and SD3, respectively). Table 4.5 presents the KS test p-values for IR and size portfolios to test the null hypothesis that the target portfolio stochastically dominates the other portfolios at the s^{th} order of the sample considered. The table shows the three results with the SD1-, SD2-, and SD3-order p-values. Risk-averse investors generally avoid risky or highly volatile stocks. as shown by the p-values.

Table 4.5: Stochastic Dominance of Idiosyncratic Risk and Size Portfolios

		Pakistan		
	IR1 *versus* IR5	**IR5 *versus* IR1**	**Size5 *versus* Size1**	**Size1 *versus* Size5**
SD Orders	**KS P-value**		**KS P-value**	
SD1	0.132	0.000	1.000	0.000
SD2	0.742	0.000	0.740	0.000
SD3	0.700	0.000	0.700	0.000
		Brazil		
SD1	0.091	0.000	1.000	0.000
SD2	0.074	0.000	0.1790	0.000
SD3	0.170	0.000	0.1670	0.000
		Russia		
SD1	0.382	0.001	1.000	0.003
SD2	0.1742	0.000	0.749	0.000
SD3	0.170	0.000	0.784	0.000
		India		
SD1	0.501	0.000	0.489	0.006
SD2	0.767	0.000	0.673	0.000
SD3	0.769	0.000	0.563	0.001

		China		
SD1	0.0187	0.009	1.000	0.000
SD2	0.0156	0.001	0.1630	0.000
SD3	0.1190	0.001	0.1835	0.000
		South Africa		
SD1	0.7828	0.001	1.000	0.003
SD2	0.8427	0.000	0.749	0.000
SD3	0.8208	0.000	0.784	0.000

Note: Stochastic dominance of two pairs of idiosyncratic risk and size portfolios. SD1, SD2, and SD3 are three p-values of stochastic orders first, second, and third.

Specifically, the *p*-values indicate that the null hypothesis that IR5 stochastically dominates IR1 is rejected, whereas the reverse null hypothesis is not rejected. These results show that IR1 stochastically dominates its counterpart portfolios. The *p*-values of the IR portfolio panel clearly show that we do not reject the null hypothesis that IR1 stochastically dominates IR5. Alternatively, we accept the hypothesis that IR1 stochastically dominates IR5, as all the values have significance levels higher than 10 percent and 5 percent, except China. In China, IR5 stochastically dominates IR1 at the 1 percent level for SD1 and SD2. At the same time, the results for size portfolios also support the presence of the IR puzzle in which Size5 portfolios stochastically dominate Size1 portfolios. These findings are significant at all levels for the full sample period. In other words, the results in the size portfolio panel reveal that Size5 dominance is more pervasive in all SD orders.

The empirical findings suggest that a portfolio of large stocks returns are significantly higher than those of small stocks. However, theoretically, it is well established that investor with having higher risk appetite requires higher returns for investing in risky assets. Since small stocks are generally considered riskier, they should offer higher returns. Nevertheless, the findings given in Table 4.3 provide clear evidence that the high IR based portfolio and small size portfolios both give lower returns than their counterpart portfolios. This evidence confirms the presence of an IR puzzle. The results indicate the presence of IR puzzle hold for all the BRICS member countries and Pakistan.

4.5.2. Idiosyncratic Risk Puzzle: Quintile Regression Approach

To examine the IR puzzle, this study focuses on quintile regressions (QR) at 20 percent, 40 percent, 60 percent, and 80 percent and OLS for comparison with quintile regression results. Table 4.6 shows the QR model results, displaying the IR relationship with stock returns. Equation (3.11) represents the quintile regression of stock returns on IR and other control variables, namely, return reversal, momentum returns, market-to-book ratio, downside co-skewness, and firm beta, using monthly frequency data.

The IR puzzle results are presented in Table 4.6. The OLS estimates show that the IR coefficients are negative and significant at all acceptable levels for all BRICS countries and Pakistan. The quantile regression estimation for all sample countries suggests that IR is a dominant predictor of response stock returns and has a significant relationship at many quantiles, including the median. For emerging countries, India and China and developing country Pakistan, the slope coefficient of IR is negative and significant from the 20^{th} to 80^{th} quantiles, including OLS estimates. In contrast, the slope coefficients of Brazil, Russia, and South Africa are negative at lower quantiles and become positive at upper quantiles. This upward trend in marginal effect coefficients can imply that in the left (right) tail of the conditional distribution of excess returns, the lower (higher) excess returns are associated with higher IR.

Theoretically, the remaining coefficients of the main variables are highly significant, with stock returns at all acceptable levels of significance. The OLS estimator predicts the mean values of stock returns, and it does not enable the examination of returns using other percentiles of distributions. This study reports the quintile estimates to check the relationship between IR and stock returns using the QR model to address this problem. The results of the QR model show significant variations in the coefficients of IR across the 20th percentile to the 80th percentile of stock returns. Specifically, we can observe from the table that the high coefficient of IR decreases with the stock returns. These results hold for all sample countries except Russia. For instance, Russia is the only country where the IR puzzle is observed for 20 percent of stock returns. The IR puzzle is found in the remaining sample countries from the 20th to the 80th quantiles.

In sum, a significant negative relationship exists between returns and the IR across different quantiles. These findings are consistent with the findings by Malagon et al. (2015), Qadan (2019), Qadan et al. (2019) and Wan (2018) based on investors' sentiments and time-varying possible justifications. Wan (2018) documented the existence of the IR anomaly in highly volatile stocks. The limits of arbitrage discourage investors from correcting potential mispricing and lead to lower future returns. Qadan et al. (2019) state that investor risk aversion is the rationale for this negative association. The increase in investors' fear gauge makes investors more risk averse, and, therefore, they diversify their investments to balance their portfolios. Malagon et al. (2018) explain that this negative relationship is due to conditional pricing of liquidity, which refers to the fact that investors frequently switch from less liquid to more liquid assets and asset classes during recessions, with a significant impact on the prices of illiquid assets or stocks with highly IR. Risk appetite is critical in explaining and forecasting this negative relationship over time. Notably, when investor risk appetite decreases, they shift their investment from less volatile to more volatile stocks, which generate positive relationship between IR and stock returns (Qadan, 2019).

These findings have important behavioural finance implications and confirm the prospect theory of Kaineman and Tversky (1979). The theory states that investors have an overwhelming propensity to be less (more) risk averse in case of profit (loss). The use of OLS and QR methods in a panel-data structure reveals that the shape of the relationship does not change and is dynamic. The relationship curves resemble the utility curves for risk seeking and risk aversion, not the attitude of risk neutrality. Our results help explain conflicting results in the literature on the shape of the idiosyncratic risk-return relation. The shape of the relationship is dynamic, which shows that IR is "priced."

Table 4.6: Identifying Idiosyncratic Risk Puzzle Through Quintile Regression

Pakistan					
	Quintiles				OLS
Variables	**20%**	**40%**	**60%**	**80%**	
Constant					0.1447 ***
					(0142)
Idiosyncratic Risk	-0.2308***	-0.1624***	-0.2123***	-0.0921***	-0.2097***
	(0.123)	(0.854)	(0.738)	(0.341)	(0196)
Return Reversal	0.1463***	0.1340***	0.1265***	0.1151***	0.1203***
	(0.174)	(0.197)	(0.175)	(0.072)	(0.215)
Momentum Returns	0.0352***	0.0378***	0.0332***	0.0322***	0.0368***
	(0.531)	(0.217)	(0.121)	(0.112)	(0.632)
Market to Book ratio	0.0482***	0.0299***	0.0607***	0.0556***	0.0178***
	(0.132)	(0.074)	(0.085)	(0.0423)	(0.231)
Downside Coskewness	-0.0589***	-0.0417***	-0.0323***	-0.0415*	-0.0789***
	(0.0275)	(0.128)	(0.198)	(0.265)	(0.421)
Systematic Risk	-0.0030*	0.0497*	0.1162***	0.0874**	0.0313**
	(0.1877)	(0.0195)	(0.2094)	(0.1770)	(0.1191)

Brazil					
	Quantiles				OLS
Variables	**20%**	**40%**	**60%**	**80%**	
Constant					0.0917*
					(0.120)
Idiosyncratic Risk	-0.1127***	-0.2412***	-0.3174***	0.3162***	-0.9714***
	(0.213)	(0.312)	(0.614)	(0.053)	(0.853)
Return Reversal	0.6375*	0.4083***	0.1265***	0.1151***	0.1203***
	(0.527)	(0.0128)	(0.328)	(0.186)	(0.179)
Momentum Returns	-0.2971**	0.0748**	0.0217**	0.0219**	0.0812**
	(0.0836)	(0.173)	(0.189)	(0.234)	(0.078)
Market to Book Ratio	0.02156*	0.0918*	0.0792*	0.0628**	0.0192**

	(0.0267)	(0.0271)	(0.0382)	(0.0282)	(0.329)
Downside Coskewness	-0.0581*	-0.0491***	-0.029***	-0.0721*	-0.0568*
	(0.090)	(0.0321)	(0.129)	(0.0215)	(0.812)
Systematic Risk	-0.0423*	-0.0142**	-0.062***	-0.0952*	-0.084*
	(0.0177)	(0.010)	(0.1754)	(0.126)	(0.631)

Russia

Variables	Quantiles 20%	40%	60%	80%	OLS
Constant					0.0348***
					(0.226)
Idiosyncratic Risk	-0.0559***	0.0346**	0.0072*	0.0221***	-0.1582***
	(0.0643)	(0.577)	(0.0248)	(0.041)	(0.152)
Return Reversal	0.01367***	0.01389***	0.02283***	0.07709***	0.0141***
	(0.0237)	(0.0372)	(0.08135)	(0.0163)	(0.139)
Momentum Returns	-0.07731***	-0.07813***	0.0907***	0.0886***	0.0708***
	(0.0175)	(0.027)	(0.021)	(0.1752)	(0.648)
Market to Book Ratio	0.182***	0.1673***	0.1877***	0.0375**	-0.202***
	(0.0372)	(0.0384)	(0.0318)	(0.0323)	(0.159)
Downside Coskewness	-0.0311***	-0.0317***	-0.0213	-0.00765	-0.298***
	(0.03918)	(0.0278)	(0.152)	(0.2165)	(0.918)
Systematic Risk	-0.01830*	-0.01672*	-0.0411*	-0.0564**	-0.0218**
	(0.0243)	(0.0291)	(0.0284)	(0.0370)	(0.0457)

India

Variables	Quantiles 20%	40%	60%	80%	OLS
Constant					0.1987*
					(0.298)
Idiosyncratic Risk	-0.193*	-0.1923**	-0.1829**	-0.2892***	-0.9194***
	(0.0562)	(0.296)	(0.927)	(0.835)	(0.296)
Return Reversal	0.1783*	0.1967*	0.1197*	0.12975**	0.1291**
	(0.672)	(0.193)	(0.193)	(0.193)	(0.1189)
Momentum Returns	0.0433*	-0.0193*	0.0198**	0.0209**	0.0922**
	(0.136)	(0.183)	(0.167)	(0.193)	(0.182)
Market to Book Ratio	0.1026*	0.1938*	0.1829*	0.1828**	0.1102**
	(0.142)	(0.121)	(0.134)	(0.129)	(0.189)
Downside Coskewness	-0.0192*	-0.178***	-0.1292***	-0.1891*	-0.1898*
	(0.189)	(0.134)	(0.119)	(0.195)	(0.189)
Systematic Risk	-0.0233*	-0.0562**	-0.0162***	-0.01672*	-0.1564*
	(0.197)	(0.189)	(0.129)	(0.1186)	(0.189)

China

Variables	Quantiles 20%	40%	60%	80%	OLS
Constant					0.0617*
					(0.230)
Idiosyncratic Risk	-0.1237***	-0.1312***	-0.1574***	-0.17162***	-0.7014***
	(0.1303)	(0.1912)	(0.1014)	(0.1953)	(0.1053)
Return Reversal	0.2315*	0.2083***	0.2195***	0.2151***	0.2203***
	(0.1027)	(0.1128)	(0.1028)	(0.1016)	(0.1109)
Momentum Returns	-0.3171**	-0.3748**	0.3217**	0.3219**	0.3812**
	(0.0186)	(0.0173)	(0.0189)	(0.0234)	(0.178)
Market to Book Ratio	0.06156*	0.0618*	0.0692*	0.0638**	0.0692**

	(0.0217)	(0.0211)	(0.0312)	(0.0482)	(0.3290)
Downside Coskewness	-0.0111*	-0.0111***	-0.0119***	-0.01121*	-0.0118*
	(0.120)	(0.132)	(0.189)	(0.215)	(0.112)
Systematic Risk	-0.1230*	-0.1420**	-0.1620***	-0.1952*	-0.0614*
	(0.0237)	(0.0210)	(0.0354)	(0.026)	(0.631)

South Africa

	Quantiles				OLS
Variables	**20%**	**40%**	**60%**	**80%**	
Constant					0.0148***
					(0.226)
Idiosyncratic Risk	-0.1059***	-0.1346**	-0.1072*	0.1221***	-0.1012***
	(0.113)	(0.107)	(0.108)	(0.141)	(0.282)
Return Reversal	0.1067***	0.1189***	0.1223***	0.1709***	0.2491***
	(0.0137)	(0.0372)	(0.08135)	(0.0163)	(0.119)
Momentum Returns	0.0341***	-0.0313***	-0.0307***	0.0306***	0.0398***
	(0.175)	(0.127)	(0.121)	(0.152)	(0.148)
Market to Book Ratio	0.1120***	0.1173***	0.1170***	0.1750**	0.1202***
	(0.0312)	(0.0314)	(0.0314)	(0.0313)	(0.209)
Downside Coskewness	-0.0303***	-0.0307***	-0.0313	-0.0365	-0.0308***
	(0.038)	(0.028)	(0.132)	(0.065)	(0.108)
Systematic Risk	-0.1030*	-0.1672*	-0.1411*	-0.1564**	-0.2180**
	(0.104)	(0.129)	(0.128)	(0.137)	(0.115)

Note: The table presents the association between stock returns and idiosyncratic risk across various quantile levels along with OLS estimates. The standard errors are presented in parenthesis. *** p<1%, ** p<5%, * p<10% shows the significance levels.

4.6. Idiosyncratic Risk Puzzle: Different Groups of Firms

Our second objective is to examine the IR puzzle at different groups of firms in Pakistan and BRICS countries. By doing this, we can compare the firm-specific risk behaviour and return patterns in different groups of firms, such as market risk, financial constraint, and liquidity position. To do so, all manufacturing firms are divided first into these groups and then into quintile IR portfolios.

Table 4.7 shows the results of the IR puzzle for liquid and illiquid firms. We distinguish the firms based on their liquidity position to look at the liquidity implications of these models for asset prices. The table lists the alpha values (abnormal return performance) and their standard errors in parentheses. These alpha values are estimated with the one- to five-factor CAPM models and the Carhart model for each IR portfolio for liquid and illiquid firms. In the IR5-IR1 column, we list the t statistics to show the difference in alpha values between the groups of firms. This column determines whether a significant difference exists in alpha values and GRS t statistics between the extreme portfolios.

The findings for liquid firms are inconsistent. Except for India and South Africa, no solid evidence of the IR puzzle emerges. For example, in the results for China, we find that the IR puzzle exists with one- and five-factors, and in Brazil, only with the one-factor CAPM model. No evidence is found for Russia. The results of illiquid firms indicate that, on average, alpha values are very significant and have systemically declining patterns in the multifactor regressions for each country, from the lowest to the highest IR. Alternatively, when IR rises, the abnormal return performance of the illiquid firms falls, indicating a negative relationship between stock returns and the IR. These results support Vidal-García, Vidal, and Nguyen (2016) findings. They documented that IR is higher in small enterprises than in large businesses, and firms with high IR have less liquidity. To put it another way, the IR causes lower liquidity.

In conclusion, even when both liquidity and IR are considered, one variable does not considerably reduce the effect of the other. Although we find that the IR puzzle is found in both liquid and illiquid firms, on average illiquid firms, have more exposure to this dilemma and have worse abnormal return performance across the BRICS countries and Pakistan.

To examine the IR puzzle based on financial constraint characteristics, we present the results in Table 4.8 by splitting the sample of firms into two groups: financial constrained

(FC) and unconstrained (FUC). The table reports the alpha values of the CAPM, the one- to the five-factor CAPM, and the Carhart model estimated based on the first sorting criteria of financial constraints. Then this sorting is further divided into quintile-based portfolios of IR. The table shows only the alpha and their standard deviations. Theoretically, FC firms should have lower returns than FUC firms. This intuition suggests that if financial constraints are severe, investors should be compensated for holding stocks whose returns positively covary with increases in financial constraints. However, we confirm that the average return for FC firms poses a challenge to existing empirical asset pricing models. In other words, the alpha values of FC firms are nonzero and statistically significant. Remarkably, abnormal performance (alpha) is the lowest in IR5 portfolios in Brazil, Russia, and India for all the estimated models (the one- to five-factor models and the Carhart model). But in China, the alpha values are lowest for the one-, two-, and five-factor CAPM models. Similarly, South Africa's lowest value is found only with the five-factor CAPM model.

The results for FUC firms also have similar results to some extent. For example, the IR puzzle is based on all asset pricing models except the Carhart model. In Russia, the puzzle is evident for all models except the one-factor CAPM model. We found mixed evidence of the puzzle in India, China, and South Africa. However, based on a comparison of alpha values, we can conclude that financially constrained firms experience higher sensitivity to IR than more financially constrained firms. On average, the less financially constraints alphas for IR5 are high for all BRICS countries. The spread between IR5 and IR1 in all capital asset pricing models is highly significant. Consequently, the GRS test strongly rejects the null hypothesis that alphas are zero, regardless of the asset model employed. In other words, the portfolio of the most financially constrained firms slightly underperforms the less constrained firms, thus providing evidence of the IR puzzle.

Predictable returns are preferred to uncertain returns. But firms make trade-offs; an uncertain strategy or investment should be used only if the predicted return is significant enough to offset the risk. The asset pricing model establishes a link between returns and volatility. It enables historical price volatility to be used as a measure of return predictability in the past. Beta or market risk measures a company's susceptibility to changes in systemic factors. To examine the sensitivity of the IR puzzle based on market risk, we divide the firms into three groups (low-, medium-, and high-beta firms) and estimate the alpha values using asset pricing models. The estimated alpha values and their standard errors are presented in Table 4.9. Any efficient asset pricing model must be able to capture all alpha values that should be zero. However, the table shows the nonzero alpha values irrespective of the beta group of firms. Overall, the findings strongly indicate the presence of the IR puzzle in high- and low-beta firms for the sample countries except for Russia.

The results for Brazil show the existence of the IR puzzle for high-beta firms in all the asset pricing models. However, we find mixed results for medium- and low-beta firms, indicating the presence of the IR puzzle; that is, the alpha values of the IR5 portfolios are higher than IR1. For India, China, and South Africa, the IR puzzle is evident in high- and medium-beta firms. This implies that high-beta firms are generally less diversified and, thus, more sensitive to IR. Further, the results of high- and low-beta firms have a systemic pattern from the IR1 to the IR5 portfolios. This implies that from the lowest to the highest IR portfolios, the alpha values of all the estimated asset pricing models decrease and are statistically significant. The results also imply that the models do not capture high IR. Based on the findings, it can be argued that all asset pricing models produce identical outcomes; only the magnitude of alpha values changes across different estimated CAPMs. Our findings are consistent with the studies of Ang et al. (2009) and Vidal-García et al. (2016). Ang et al. (2009) found the IR puzzle for 23 developed markets. The effect is individually significant in each G7 country. In the United States, they rule out explanations based on trading frictions, information dissemination, and higher moments indicating a strong covariation in the low returns to high-idiosyncratic-volatility stocks across countries. Vidal-García et al. (2016). reported evidence that idiosyncratic risk is negatively related to expected returns for 728 UK mutual funds classes. They also documented the justification of the IR puzzle tax-loss selling hypothesis.

Table 4.7: Idiosyncratic Risk Puzzle in Liquid and Illiquid Firms

Portfolios / Models	Liquid Firms						Illiquid Firms					
	IR1	IR2	IR3	IR4	IR5	IR5-IR1	IR1	IR2	IR3	IR4	IR5	IR5-IR1
Pakistan												
One-Factor CAPM	0.3217*** (0.155)	0.3124* (1.231)	0.3142* (0.562)	0.298 (0.352)	0.3427* (0.218)	0.021 (10.895)	0.3057*** (0.021)	0.3816* (0.078)	0.3728** (0.082)	0.3627** (0.081)	0.2196** (0.071)	-0.0861 (0.783)
Three-Factor CAPM	-0.4029*** (0.439)	-0.4211* (0.362)	-0.4231* (0.372)	-0.4021* (0.245)	-0.4182** (0.356)	-0.015 (12.985)	-0.4016*** (0.621)	-0.4193** (0.682)	-0.4821** (0.637)	-0.4924* (0.628)	-0.5027** (0.723)	-0.1011 (4.06)
Four-Factor Carhart	-3.0098*** (0.222)	-3.1078** (0.327)	-0.3218** (0.318)	-3.2816* (0.3926)	-3.926* (0.362)	-0.916 (10.052)	-2.9756*** (0.302)	-1.9262* (0.318)	-2.5182* (0.391)	-2.8364* (0.318)	-2.816* (0.398)	-0.6184 (8.564)
Four-Factor CAPM	-1.9103*** (0.253)	-0.9264* (0.271)	-1.9261* (0.292)	-1.9783** (0.281)	-1.9272* (0.223)	-0.0169 (9.86)	-1.8228*** (0.354)	-1.8242* (0.382)	-1.9263* (0.381)	-1.3672* (0.317)	-1.9571* (0.296)	-0.1343 (6.354)
Five-Factor CAPM	-1.1357*** (0.251)	-1.6239* (0.281)	-1.6292** (0.267)	-1.8922* (0.281)	-1.2815** (0.281)	-0.145 (6.894)	-1.1383*** (0.356)	-1.1825* (0.357)	-1.8183* (0.392)	-1.9268** (0.379)	-1.9781* (0.354)	-0.8398 (5.865)
Brazil												
One-Factor CAPM	-0.931*** (0.727)	-0.924*** (0.313)	-0.971*** (0.116)	-1.017*** (0.111)	-0.912*** (0.129)	0.019 (61.786)	-0.940*** (0.121)	-0.918*** (0.147)	-0.992*** (0.162)	-0.859*** (0.182)	-1.104*** (0.149)	-0.164 (23.785)
Three-Factor CAPM	-0.956*** (0.918)	-0.964*** (0.405)	-0.924*** (0.117)	-0.987*** (0.118)	-0.918*** (0.135)	0.038 (23.985)	-0.970*** (0.184)	-0.925*** (0.148)	-0.995*** (0.173)	-0.816*** (0.160)	-0.972*** (0.159)	-0.002 (45.097)
Four-Factor Carhart	0.965* (0.193)	0.980 (0.878)	0.854*** (0.1001)	0.842*** (0.894)	0.869*** (0.398)	-0.096 (33.987)	1.266*** (0.603)	1.679*** (0.822)	1.211*** (0.119)	0.901*** (0.121)	0.652 (0.135)	-0.614 (23.895)
Four-Factor CAPM	-0.988 (0.976)	-0.970*** (0.398)	-0.828*** (0.131)	-0.850*** (0.131)	-0.996** (0.133)	-0.016 (56.869)	-0.977*** (0.113)	-0.928*** (0.170)	-0.788*** (0.174)	-0.727*** (0.165)	-0.979*** (0.183)	-0.002 (23.986)
Five-Factor CAPM	-0.948 (0.939)	-0.887* (0.385)	-0.825*** (0.134)	-0.851*** (0.133)	-0.892** (0.131)	0.056 (23.897)	-0.917*** (0.113)	-0.930*** (0.170)	-0.786*** (0.176)	-0.722*** (0.167)	-1.072*** (0.191)	-0.155 (12.896)
Russia												
One-Factor CAPM	0.0406 (0.416)	0.0405 *** (0.689)	0.0513 (0.586)	0.0545* (0.464)	0.0403*** (0.041)	-0.003 (11.678)	-0.0411 (0.417)	-0.0469 (0.446)	0.0434 (0.444)	0.0474 (0.463)	-0.0479 (0.607)	-0.0068 (56.323)
Three-Factor CAPM	-0.0393 (0.46)	-0.0373* (0.762)	-0.03189 (0.061)	-0.0302* (0.005)	-0.0398** (0.429)	-0.0005 (34.875)	-0.0327** (0.443)	-0.0317** (0.459)	0.0374* (0.483)	0.0308* (0.498)	-0.0334* (0.657)	-0.0007 (11.879)
Four-Factor Carhart	0.0301*** (0.239)	0.0327*** (0.283)	0.200*** (0.218)	0.0396** (0.197)	0.0300*** (0.155)	-0.0001 (34.785)	0.0230*** (0.166)	0.0205*** (0.189)	0.0209** (0.198)	0.0212*** (0.176)	0.0202*** (0.289)	-0.0028 (34.875)
Four-Factor CAPM	-0.0354* (0.545)	-0.0316*** (0.608)	-0.0391*** (0.505)	-0.0362*** (0.422)	-0.0393*** (0.361)	-0.0039 (63.987)	0.0459*** (0.307)	0.0498* (0.455)	0.0319*** (0.525)	0.0321*** (0.547)	0.0334** (0.682)	-0.0125 (5.876)

Five-Factor CAPM	-0.0409* (0.534)	0.0408*** (0.554)	0.0478*** (0.498)	0.0340*** (0.419)	0.0409*** (0.358)	0.0818 (9.453)	0.0488*** (0.307)	0.0496* (0.454)	0.0320*** (0.537)	0.0360*** (0.534)	0.0309* (0.657)	-0.0179 (23.987)
India												
One-Factor CAPM	-0.536*** (0.013)	-0.532*** (0.118)	-0.527*** (0.119)	-0.524*** (0.117)	-0.522*** (0.106)	-0.014 (11.786)	-0.516*** (0.169)	-0.526*** (0.170)	-0.534*** (0.213)	-0.541*** (0.101)	-0.532*** (0.145)	-0.016 (45.987)
Three-Factor CAPM	-0.505*** (0.108)	-0.498*** (0.091)	-0.498*** (0.071)	-0.507*** (0.061)	-0.510*** (0.081)	-0.005 (2.876)	-0.500*** (0.055)	-0.507*** (0.053)	-0.513 (0.077)	-0.514*** (0.087)	-0.597*** (0.078)	-0.0970 (34.897)
Four-Factor Carhart	0.496*** (0.153)	0.431*** (0.129)	0.316*** (0.104)	0.264*** (0.796)	0.282*** (0.689)	-0.214 (44.897)	0.360*** (0.702)	0.306*** (0.788)	0.319*** (0.955)	0.327*** (0.114)	0.336*** (0.179)	0.0696 (11.875)
Four-Factor CAPM	-0.512*** (0.108)	-0.503*** (0.118)	-0.502*** (0.170)	-0.510*** (0.160)	-0.513*** (0.517)	-0.001 (11.345)	-0.503*** (0.597)	-0.511*** (0.603)	-0.517*** (0.619)	-0.517*** (0.811)	-0.521*** (0.117)	-0.0180 (11.765)
Five-Factor CAPM	-0.452*** (0.107)	-0.443*** (0.097)	-0.449*** (0.073)	-0.462*** (0.613)	-0.457*** (0.517)	-0.005 (22.987)	-0.452*** (0.571)	-0.461*** (0.622)	-0.460*** (0.716)	-0.463*** (0.836)	-0.462*** (0.114)	-0.010 (11.908)
China												
One-Factor CAPM	-0.0209** (0.827)	-0.0286*** (0.824)	-0.0371*** (0.775)	-0.0420*** (0.751)	-0.0237*** (0.659)	-0.0028 (23.987)	-0.0405*** (0.672)	-0.0438** (0.758)	-0.0400*** (0.805)	-0.0457*** (0.888)	-0.0427*** (0.975)	-0.0022 (11.897)
Three-Factor CAPM	-0.0299*** (0.819)	-0.0352*** (0.829)	-0.0430*** (0.778)	-0.0464*** (0.676)	-0.0296*** (0.679)	-0.0004 (11.456)	-0.0443*** (0.675)	-0.0481*** (0.074)	-0.0403*** (0.081)	-0.0411*** (0.089)	-0.0465*** (0.096)	-0.0022 (7.908)
Four-Factor Carhart	0.0459 (0.162)	-0.0505 (0.1573)	0.0944 (0.140)	-0.0920 (0.139)	0.0648 (0.114)	0.0189 (11.786)	-0.0618 (0.1224)	0.0900 (0.132)	0.0689 (0.149)	0.0705 (0.162)	0.0702 (0.1947)	0.1320 (5.786)
Four-Factor CAPM	-0.0277* (0.801)	-0.0317*** (0.816)	-0.0396*** (0.762)	-0.0456**** (0.744)	-0.0251*** (0.671)	-0.0026 (23.987)	-0.0354*** (0.676)	-0.0354*** (0.739)	-0.0381*** (0.788)	-0.0328*** (0.855)	-0.0381*** (0.938)	-0.0027 (9.876)
Five-Factor CAPM	-0.0702*** (0.881)	-0.0785** (0.88)	-0.0840*** (0.814)	-0.0945*** (0.793)	-0.0876*** (0.072)	-0.0174 (9.876)	-0.0879*** (0.714)	-0.0729*** (0.797)	-0.0774*** (0.832)	-0.0999*** (0.931)	-0.0938*** (0.100)	0.1817 (4.786)
South Africa												
One-Factor CAPM	0.0297*** (0.481)	0.0261*** (0.433)	0.0210*** (0.419)	0.0121*** (0.265)	0.0112*** (0.211)	-0.0185 (6.453)	0.0130*** (0.227)	0.0181*** (0.309)	0.0120*** (0.333)	0.01208*** (0.385)	0.0127*** (0.343)	-0.0003 (6.786)
Three-Factor CAPM	0.0233*** (0.430)	0.0181*** (0.440)	0.0152*** (0.343)	0.0866*** (0.286)	0.0855*** (0.202)	0.0622 (3.487)	0.0103*** (0.229)	0.0103*** (0.298)	0.0101*** (0.321)	0.0101*** (0.363)	0.0101*** (0.332)	-0.0002 (9.786)
Four-Factor Carhart	-0.0190*** (0.555)	-.0.0173*** (0.576)	-.0.0833*** (0.517)	-0.0681*** (0.398)	-0.0556*** (0.300)	-0.0366 (7,456)	-0.0439*** (0.322)	-0.0447*** (0.427)	-0.0427*** (0.462)	-0.0449*** (0.537)	-0.0479*** (0.511)	-0.0040 (4.987)
Four-Factor CAPM	0.0214*** (0.427)	0.0172*** (0.460)	0.0143*** (0.343)	0.083*** (0.270)	0.081*** (0.230)	-0.0596 (3.984)	0.098*** (0.231)	0.013*** (0.239)	0.0102*** (0.320)	0.014*** (0.363)	0.011*** (0.335)	-0.087 (3.999)
Five-Factor CAPM	0.0203*** (0.454)	0.0168*** (0.434)	0.0149*** (0.372)	0.094*** (0.294)	0.086*** (0.222)	0.0657 (8.934)	0.0104*** (0.245)	0.012*** (0.323)	0.013*** (0.349)	0.016** (0.395)	0.012*** (0.371)	-0.0016 (3.876)

Note: The table presents the results of IR puzzle based on bivariate portfolio analysis. The full sample is divided into liquid and illiquid firms then these two groups are further divided into quintile portfolios of IR for all manufacturing firms of BRICS countries. Alpha is estimated using one factor to five factors CAPM models and presented along with their standard errors below in parentheses. ***, **, * shows the level of significance for 1%, 5%, and 10% respectively.

Table 4.8: Idiosyncratic Risk Puzzle in Financially Constrained and Unconstrained Firms

	Financially Constrained Firms						Financially Unconstrained Firms					
Portfolios / Models	IR1	IR2	IR3	IR4	IR5	IR5-IR1	IR1	IR2	IR3	IR4	IR5	IR5-IR1
Pakistan												
One-Factor CAPM	0.3181*** (0.108)	0.3562* (0.192)	0.2622* (0.178)	0.2725* (0.167)	0.2816 (0.135)	-0.0365 (6.78)	0.2765*** (0.106)	0.2826* (0.138)	0.3721** (0.173)	0.2173* (0.183)	0.2193** (0.173)	-0.0572 (5.96)
Three-Factor CAPM	-0.4221*** (0.321)	-0.4216* (0.342)	-0.5622* (0.527)	-0.472* (0.678)	-0.4823* (0.567)	-0.0602 (6.97)	-0.4220*** (0.311)	-0.4183* (0.317)	-0.4067* (0.382)	-0.4183** (0.356)	-0.4382* (0.372)	-0.0162 (13.97)
Four-Factor Carhart	-2.8519** (0.149)	-2.8162* (0.163)	-2.6821* (0.173)	-2.8153* (0.172)	-2.825* (0.272)	0.0269 (5.87)	-2.8409** (0.150)	-2.782* (0.163)	-2.5622* (0.184)	-2.7842* (1.476)	-2.9242** (2.624)	-0.0833 (14.97)
Four-Factor CAPM	-1.6437** (0.172)	-1.6287* (0.183)	-1.5243* (0.184)	-1.5733** (0.183)	-1.3826 (0.186)	0.2611 (11.97)	-1.6478** (0.575)	-1.6284** (0.692)	-1.9274 (0.672)	-1.9254* (0.782)	-1.9193** (0.724)	-0.2715 (5.85)
Five-Factor CAPM	-0.8214*** (0.164)	-0.9373* (0.127)	-0.9271* (0.173)	-0.8252* (0.128)	-0.8262** (0.184)	-0.0048 (7.96)	-0.7932*** (0.159)	-0.8264* (0.167)	-0.8573* (0.183)	-0.8392* (0.294)	-0.8329* (0.284)	-0.0397 (13.87)
Brazil												
One-Factor CAPM	-0.9683*** (0.188)	-0.9211*** (0.127)	-0.9476*** (0.129)	-0.9620*** (0.138)	-0.9709*** (0.168)	-0.0026 (4.675)	-0.9249*** (0.134)	-0.9808*** (0.171)	-0.9609*** (0.165)	-0.9358*** (0.015)	-0.9384*** (0.129)	-0.0135 (9.693)
Three-Factor CAPM	-0.9348*** (0.127)	-0.8752*** (0.125)	-0.9051*** (0.126)	-0.9328*** (0.139)	-0.9353*** (0.169)	0.0005 (4.987)	-0.8954*** (0.013)	-0.9482*** (0.171)	-0.9268*** (0.171)	-0.8840*** (0.149)	-0.8982*** (0.129)	-0.0028 (6.897)
Four-Factor Carhart	0.7768*** (0.129)	0.4033*** (0.968)	0.6326*** (0.972)	0.7063*** (0.998)	0.6766*** (0.117)	-0.1002 (3.984)	0.6958*** (0.093)	0.8489*** (0.116)	0.6584*** (0.121)	0.4020*** (0.114)	0.5549*** (0.984)	1.2507 (3.976)
Four-Factor CAPM	-0.8167*** (0.209)	-0.7866*** (0.014)	-0.7884*** (0.014)	-0.8050*** (0.155)	-0.8248*** (0.188)	-0.0081 (9.074)	-0.7785*** (0.141)	-0.8130*** (0.019)	-0.8146*** (0.189)	-0.7911*** (0.166)	-0.7938*** (0.142)	-0.0153 (6.956)
Five-Factor CAPM	-0.8141*** (0.211)	-0.7845*** (0.143)	-0.7835*** (0.143)	-0.8023*** (0.158)	-0.8235*** (0.191)	-0.0094 (4.984)	-0.7754*** (0.143)	-0.8111*** (0.194)	-0.8136*** (0.192)	-0.7883*** (0.169)	-0.7896*** (0.145)	-0.0142 (5.895)

Russia												
One-Factor CAPM	0.0503*** (0.355)	-0.0535*** (0.287)	-0.0564* (0.315)	-0.0555* (0.376)	-0.0573*** (0.469)	-0.007 (76.896)	-0.0439*** (0.307)	-0.0461** (0.382)	-0.0428*** (0.346)	-0.0446*** (0.296)	-0.0436*** (0.266)	-0.0003 (66.574)
Three-Factor CAPM	0.0348*** (0.366)	-0.0303*** (0.303)	-0.0393*** (0.332)	-0.0339*** (0.390)	-0.0325*** (0.491)	-0.0023 (45.876)	-0.0323*** (0.333)	-0..0319*** (0.431)	-0.02212*** (0.387)	-0.0460*** (0.331)	-0.0417*** (0.029)	-0.0094 (43.976)
Four-Factor Carhart	0.0212*** (0.119)	0.0160*** (0.109)	0.0155*** (0.117)	0.0174*** (0.134)	0.0129*** (0.142)	-0.0083 (12.897)	0.0222*** (0.134)	0.0258*** (0.196)	0.0219*** (0.176)	0.0190*** (0.140)	0.0148*** (0.134)	-0.0074 (16.987)
Four-Factor CAPM	0.0418*** (0.328)	0.0405*** (0.243)	0.0369*** (0.261)	0.0413*** (0.301)	0.0359*** (0.345)	-0.0059 (33.984)	0.0445*** (0.267)	0.0283*** (0.399)	0.0251*** (0.369)	0.0399*** (0.303)	0.0434*** (0.027)	-0.0011 (34.987)
Five-Factor CAPM	0.0418*** (0.328)	0.0406*** (0.242)	0.0364*** (0.260)	0.0408*** (0.302)	0.0359** (0.345)	-0.0059 (9.673)	0.0416*** (0.262)	0.0384*** (0.404)	0.0338*** (0.366)	0.0378*** (0.294)	0.0377*** (0.264)	-0.0039 (11.786)
India												
One-Factor CAPM	-0.5222*** (0.056)	-0.5297*** (0.057)	-0.5310*** (0.051)	-0.5317*** (0.052)	-0.5288*** (0.051)	-0.066 (13.876)	-0.5243*** (0.041)	-0.5225*** (0.049)	-0.5238*** (0.050)	-0.5240*** (0.044)	-0.5251*** (0.047)	-0.0008 (11.871)
Three-Factor CAPM	-0.5032*** (0.042)	-0.5103*** (0.048)	-0.5078*** (0.056)	-0.5043*** (0.051)	-0.5021 (0.049)	-0.001 (15.987)	-0.5015*** (0.042)	-0.5001*** (0.038)	-0.5042*** (0.036)	-0.5060*** (0.034)	-0.5083*** (0.036)	-0.0068 (16.109)
Four-Factor Carhart	0.2988*** (0.059)	0.2784*** (0.063)	0.2821*** (0.068)	0.3103*** (0.079)	0.2871*** (0.068)	-0.0117 (15.456	0.3969*** (0.051)	0.3090*** (0.005)	0.3083*** (0.048)	0.2993*** (0.045)	0.2136*** (0.048)	-0.1833 (17.382)
Four-Factor CAPM	-0.5073*** (0.048)	-0.5132*** (0.047)	-0.5109*** (0.054)	-0.5064*** (0.057)	-0.5051*** (0.048)	-0.0023 (18.382)	-0.5048*** (0.039)	-0.5041 (0.037)	-0.5079*** (0.035)	-0.5098*** (0.036)	-0.5118 (0.035)	-0.007 (19.283)
Five-Factor CAPM	-0.4566*** (0.046)	-0.4624*** (0.047)	-0.4589*** (0.052)	-0.4469*** (0.068)	-0.4487*** (0.046)	0.0079 (11.378)	-0.4523*** (0.039)	-0.4505*** (0.040)	-0.4546*** (0.036)	-0.4589*** (0.043)	-0.4590*** (0.036)	-0.0067 (13.292)
China												
One-Factor CAPM	-0.0412*** (0.0307)	-0.0418*** (0.0207)	-0.0422*** (0.0277)	-0.0425*** (0.0397)	-0.0428*** (0.0317)	-0.0016 (23.281)	-0.0332*** (0.052)	-0.0338*** (0.053)	-0.0332*** (0.053)	-0.0335*** (0.059)	-0.0338*** (0.051)	-0.0006 (25.982)
Three-Factor CAPM	-0.0314*** (0.039)	0.0324*** (0.039)	0.0334*** (0.048)	0.0384*** (0.049)	0.0404*** (0.046)	0.0718 (26.291)	-0.0334*** (0.039)	-0.0337*** (0.039)	-0.0338*** (0.048)	-0.0340*** (0.049)	-0.0400*** (0.046)	-0.0066 (29.387)
Four-Factor Carhart	-0.0493 (0.035)	-0.0393 (0.031)	-0.0383 (0.039)	-0.0399 (0.040)	-0.0403 (0.041)	-0.009 (4.987)	-0.0390 (0.038)	-0.0398 (0.039)	-0.0388 (0.040)	-0.0409 (0.049)	-0.0413 (0.051)	-0.0023 (9.675)
Four-Factor CAPM	-0.0496*** (0.031)	-0.506*** (0.033)	-0.0512*** (0.036)	-0.0534*** (0.037)	-0.0567*** (0.039)	-0.0071 (5.897)	-0.0413*** (0.039)	-0.0416*** (0.036)	-0.0418*** (0.039)	-0.0504*** (0.047)	-0.0507*** (0.049)	-0.0094 (4.987)
Five-Factor CAPM	-0.0776*** (0.037)	-0.0785*** (0.035)	-0.0789*** (0.037)	-0.0806*** (0.043)	-0.0811*** (0.044)	-0.0035 (8.567)	-0.0721*** (0.047)	-0.0725*** (0.045)	-0.0727*** (0.047)	-0.0801*** (0.043)	-0.0808*** (0.044)	-0.0087 (9.673)
South Africa												

One-Factor CAPM	0.0158*** (0.1590)	0.0171*** (0.147)	0.0175*** (0.151)	0.0165*** (0.163)	0.0193*** (0.220)	-0.0035 (5.483)	0.0192*** (0.294)	0.0171*** (0.342)	0.0174*** (0.320)	0.0147*** (0.2500)	0.0095*** (0.169)	-0.0097 (6.373)
Three-Factor CAPM	0.0130*** (0.155)	0.0137*** (0.144)	0 .0132*** (0.147)	0.0113*** (0.160)	0.0114*** (0.221)	-0.0016 (7.372)	0.0138*** (0.300)	0.0108*** (0.352)	0.0123*** (0.339)	0.0112*** (0.249)	0.0119*** (0.164)	-0.0019 (9.783)
Four-Factor Carhart	-0.0934*** (0.219)	-0.0872*** (0.208)	-0.0887*** (0.212)	-0.0925*** (0.228)	-0.0975*** (0.300)	-0.1909 (9.372)	-0.0653*** (0.427)	-0.0626*** (0.513)	-0.0771*** (0.502)	-0.0844*** (0.400)	-0.0814*** (0.261)	-0.0161 (6.382)
Four-Factor CAPM	0.0120*** (0.157)	0.0129*** (0.145)	0.0124*** (0.148)	0.0106*** (0.161)	0.0107*** (0.222)	-0.0013 (9.673)	0.0137*** (0.300)	0.0104*** (0.350)	0.0121*** (0.380)	0.0111*** (0.249)	0.0114** (0.164)	-0.0023 (9.672)
Five-Factor CAPM	0.0117*** (0.169)	0.0125*** (0.158)	0.0126*** (0.161)	0.0119*** (0.175)	0.0122*** (0.238)	0.0005 (8.378)	0.0140*** (0.319)	0.0106*** (0.369)	0.0126*** (0.369)	0.0121*** (0.273)	0.0109*** (0.183)	-0.0031 (5.393)

Note: The table presents the results of the IR puzzle based on bivariate portfolio analysis. The full sample is divided into financially constrained and unconstrained firms then these two groups are further divided into quintile portfolios of IR for all manufacturing firms of Pakistan and BRICS countries. Alpha is estimated using one factor to five factors CAPM models and presented along with their standard errors below in parentheses. ***, **, * shows the level of significance for 1%, 5%, and 10% respectively.

Table 4.9: Idiosyncratic Risk Puzzle in High, Medium, and Low Beta Firms

Portfolios / Models	High Beta Firms						Medium Beta Firms						Low Beta Firms					
	IR1	IR2	IR3	IR4	IR5	IR5-IR1	IR1	IR2	IR3	IR4	IR5	IR5-IR1	IR1	IR2	IR3	IR4	IR5	IR5-IR1
Pakistan																		
One-Factor CAPM	0.2619** (0.134)	0.267* (0.165)	0.342* (0.175)	0.453* (0.187)	0.2613* (0.136)	-0.0006 (5.87)	0.2152*** (0.191)	0.2741* (0.168)	0.2816* (0.183)	0.2728* (0.118)	0.2849* (0.142)	0.0697 (14.97)	0.3754** (0.152)	0.3716* (0.178)	0.5274* (0.184)	0.7283* (0.122)	0.4722* (0.143)	0.0968 (4.98)
Three-Factor CAPM	-0.387*** (0.360)	-0.363* (0.374)	-0.385* (0.649)	-0.376* (0.785)	-0.328* (0.684)	0.059 (4.78)	-0.3732** (0.328)	-0.3728* (0.362)	-3.287* (0.283)	-0.3824* (0.292)	-0.3924* (0.259)	-0.0192 (5.98)	-0.3944*** (0.431)	-0.3827* (0.462)	-0.3862** (0.382)	-0.419* (0.382)	-0.482* (0.327)	-0.0876 (4.98)
Four-Factor Carhart	-2.7423** (0.233)	-2.5489* (0.276)	-2.853* (0.286)	-2.573* (0.231)	-2.7849* (0.265)	-0.0426 (10.89)	-2.9088*** (0.163)	-2.927* (0.194)	-2.824* (0.183)	-2.927* (0.173)	-2.5733* (0.192)	0.3355 (5.78)	-2.9593** (0.177)	-2.6832* (0.156)	-2.8254* (0.187)	-2.682* (0.163)	-2.816* (0.283)	0.1433 (5.89)
Four-Factor CAPM	-1.6754** (0.264)	-1.7478* (0.352)	-1.8474* (0.362)	-1.8468* (0.341)	-1.6747* (0.342)	-0.0007 (3.78)	-1.7643*** (0.189)	-1.8264* (0.163)	-0.1836* (0.188)	-0.1682* (0.191)	-0.1826* (0.281)	1.5817 (14.98)	-1.7976** (0.243)	-1.7925* (0.283)	-1.7623* (0.284)	-0.1946* (0.219)	-0.2017* (0.2816)	1.5959 (13.98)
Five-Factor CAPM	-1.0200** (0.263)	-1.026* (0.231)	-1.6873* (0.251)	-1.5848* (0.274)	-1.6743* (0.2746)	-0.6543 (7.98)	-1.2558*** (0.200)	-1.6283* (0.183)	-1.827* (0.134)	-1.5613* (0.154)	-1.5722* (0.189)	-0.3164 (6.45)	-1.0331*** (0.226)	-1.0562* (0.317)	-1.368** (0.428)	-1.2932* (0.482)	-1.2947* (0.483)	-0.213 (7.98)
Brazil																		
One Factor CAPM	-0.786*** (0.392)	-0.803*** (0.284)	-0.803*** (0.284)	-0.802*** (0.291)	-0.930*** (0.253)	-0.144 (3.23)	-0.951*** (0.133)	-0.957*** (0.142)	-0.945*** (0.145)	-0.936*** (0.14)	-0.944*** (0.149)	0.007 (4.78)	-0.884*** (0.254)	-0.905*** (0.238)	-0.936*** (0.208)	-0.92** (0.208)	-0.923** (0.183)	-0.039 (5.29)
Three Factor CAPM	-0.890*** (0.158)	-0.376*** (0.180)	-0.871** (0.119)	-0.811** (0.139)	-0.920*** .0 147)	-0.030 (5.48)	-0.922** (0.613)	-0.917** (0.648)	-0.918** (0.668)	-0.903** (0.639)	-0.901** (0.694)	0.021 (6.48)	-0.895** (0.125)	-0.892** (0.102)	-0.884** (0.093)	-0.876** (0.101)	-0.904** (0.097)	-0.009 (7.48)
Four Factor Carhart	0.733** (0.911)	0.346** (0.608)	0.874** (0.696)	0.766*** (0.646)	0.712** (0.655)	-0.021 (8.37)	0.794** (0.465)	0.788** (0.527)	0.746* (0.553)	0.792*** (0.562)	0.798** (0.599)	1.586 (8.56)	0.657*** (0.939)	0.388** (0.849)	0.188*** (0.816)	0.294** (0.810)	0.598** (0.754)	-0.059 (8.38)
Four Factor CAPM	-0.772*** (0.157)	-0.380*** (0.166)	-0.780** (0.120)	-0.710*** (0.132)	-0.774*** (0.138)	-0.02 (7.39)	-0.820*** (0.677)	-0.814*** (0.712)	-0.815*** (0.743)	-0.826*** (0.715)	-0.839** (0.764)	-0.019 (9.57)	-0.747*** (0.134)	-0.773*** (0.118)	-0.767*** (0.105)	-0.746*** (0.112)	-0.767*** (0.109)	-0.020 (4.28)
Five Factor CAPM	-0.768*** (0.156)	-0.380*** (0.166)	-0.780*** (0.121)	-0.712*** (0.132)	-0.791** (0.139	-0.023 (8.46)	-0.821*** (0.689)	-0.816*** (0.726)	-0.814*** (0.759)	-0.823*** (0.730)	-0.838*** (0.782)	-0.017 (8.56)	-0.745*** (0.134)	-0.772*** (0.119)	-0.764*** (0.106)	-0.743*** (0.113)	-0.759*** (0.109)	-0.014 (8.28)
Russia																		

One Factor CAPM	-0.014** (0.051)	0.037 (0.047)	0.014 (0.049)	0.041 (0.048)	-0.112** (0.048)	-0.098 (9.34)	-0.024 (0.305)	-0.012* (0.029)	-0.015* (0.029)	0.0145 (0.027)	0.0143 (0.030)	0.0383 (4.29)	-0.014* (0.051)	0.0379 (0.047)	0.014 (0.045)	0.014 (0.044)	-0.015* (0.048)	-0.003 (9.47)
Three Factor CAPM	-0.094* (0.058)	0.085* (0.049)	0.046 (0.034)	0.080* (0.045)	- 0.098* (0.041)	-0.004 (4.39)	-0.055** (0.036)	-0.015* (0.037)	-0.019* (0.031)	-0.0200* (0.032)	-0.0213 ().032)	0.0337 (8.49)	0.010* (0.067)	0.012 (0.065)	-0.0131* (0.063)	-0.038*** (0.056)	-0.026** (0.076)	-0.036 (4.39)
Four Factor Carhart	0.016*** (0.169)	0.019** (0.151)	0.011*** (0.144)	0.012*** (0.143)	0.009** (0.151)	-0.007 (8.48)	0.020** (0.128)	0.014*** (0.141)	0.014*** (0.149)	0.010*** (0.144)	0.010** (0.134)	-0.010 (4.29)	0.015** (0.215)	0.019** (0.216)	0.025** (0.222)	0.026** (0.216)	0.028*** (0.196)	0.013 (6.48)
Four Factor CAPM	0.027* (0.413)	0.048** (0.353)	0.035* (0.345)	0.037* (0.354)	0.022* (0.344)	-0.005 (8.48)	0.045* (0.281)	0.025* (0295)	0.020* (0.306)	0.027** (0.281)	0.027** (0.287)	-0.018 (4.58)	0.047** (0.043)	0.052* (0.045)	0.052** (0.045)	0.051** (0.049)	0.073* (0.047)	0.026 (8.99)
Five Factor CAPM	0.027*** (0.041)	0.049*** (0.035)	0.035*** (0.034)	0.037** (0.032)	0.022*** (0.034)	0.005 (4.48)	0.043*** (0.027)	0.023*** (0.029)	0.018*** (0.030)	0.024*** (0.028)	0.027** (0.028)	-0.016 (8.49)	0.049*** (0.044)	0.055*** (0.044)	0.052*** (0.044)	0.050*** (0.049)	0.078*** (0.045)	0.029 (11.19)
India																		
One Factor CAPM	-0.586*** (0.106)	-0.569*** (0.107)	-0.554*** (0.105)	-0.544** (0.104)	-0.539** (0.103)	0.049 (9.34)	-0.504** (0.105)	-0.501** (0.130)	-0.503*** (0.140)	-0.508** (0.123)	-0.507** (0.104)	-0.003 (7.49)	-0.510** (0.096)	-0.513** (0.102)	-0.512* (0.118)	-0.511** (0.127)	-0.515* (0.192)	-0.005 (8.48)
Three Factor CAPM	-0.503*** (0.176)	-0.509*** (0.117)	-0.512*** (0.155)	-0.513** (0.124)	-0.530** (0.113)	-0.027 (8.49)	-0.413*** (0.176)	-0.429*** (0.117)	-0.482*** (0.155)	-0.493** (0.124)	-0.490** (0.113)	-0.077 (8.48)	-0.411*** (0.099)	-0.421*** (0.104)	-0.481*** (0.105)	-0.492** (0.104)	-0.499** (0.103)	-0.088 (8.39)
Four Factor Carhart	0.218*** (0.159)	0.217*** (0.163)	0.221*** (0.118)	0.213*** (0.169)	0.201*** (0.168)	-0.017 (8.49)	0.318*** (0.019)	0.317*** (0.023)	0.321*** (0.018)	0.313*** (0.029)	0.301*** (0.028)	-0.017 (4.90)	0.301*** (0.119)	0.333*** (0.123)	0.324*** (0.118)	0.310*** (0.119)	0.311*** (0.128)	0.010 (8.39)
Four Factor CAPM	-0.413*** (0.106)	-0.439*** (0.107)	-0.412*** (0.195)	-0.443** (0.104)	-0.430** (0.143)	-0.017 (4.98)	-0.393*** (0.123)	-0.399*** (0.114)	-0.322*** (0.115)	-0.343** (0.113)	-0.530** (0.103)	-0.137 (9.48)	-0.313** (0.111)	-0.319* (0.134)	-0.312* (0.105)	-0.323** (0.103)	-0.410* (0.113)	-0.097 (6.30)
Five Factor CAPM	-0.432*** (0.117)	-0.436*** (0.112)	-0.419*** (0.115)	-0.448** (0.114)	-0.450** (0.163)	-0.018 (9.40)	-0.402*** (0.170)	-0.336*** (0.120)	-0.400*** (0.150)	-0.408** (0.140)	-0.483** (0.120)	-0.081 (7.49)	-0.421* (0.160)	-0.316 (0.110)	-0.340* (0.115)	-0.318* (0.114)	-0.429** (0.110)	-0.008 (9.48)
China																		
One Factor CAPM	-0.041* (0.031)	-0.041* (0.030)	-0.0431* (0.033)	-0.044* (0.034)	-0.049* (0.033)	-0.008 (7.58)	-0.043* (0.131)	-0.041* (0.100)	-0.042* (0.107)	-0.044* (0.134)	-0.059* (0.143)	-0.016 (8.56)	-0.051* (0.103)	-0.053* (0.104)	-0.051* (0.118)	-0.052* (0.117)	-0.054* (0.114)	-0.003 (6.46)
Three Factor CAPM	-0.034** (0.033)	-0.0361* (0.031)	-0.0331* (0.033)	-0.034* (0.039)	-0.038* (0.040)	-0.004 (6.98)	-0.041** (0.112)	-0.049** (0.118)	-0.045** (0.117)	-0.045** (0.104)	-0.039** (0.173)	-0.002 (6.89)	-0.06-* (0.122)	-0.060* (0.114)	-0.061* (0.108)	-0.064* (0.100)	-0.068* (0.106)	-0.008 (7.89)
Four Factor Carhart	-0.049** (0.050)	-0.038* (0.052)	-0.030** (0.061)	-0.037** (0.062)	-0.039* (0.063)	-0.010 (9.78)	-0.051* (0.055)	-0.0310 (0.056)	-0.038 (0.054)	-0.034* (0.051)	-0.051** (0.050)	0.000 (8.78)	-0.040* (0.057)	-0.048* (0.052)	-0.041** (0.051)	-0.401** (0.052)	-0.049* (0.053)	0.009 (6.90)
Four Factor CAPM	-0.046* (0.031)	-0.046* (0.035)	-0.053* (0.036)	-0.055* (0.034)	-0.056** (0.036)	-0.010 (8.67)	-0.041* (0.038)	-0.049 (0.039)	-0.043* (0.046)	-0.045* (0.044)	-0.046** (0.026)	-0.005 (9.78)	-0.051* (0.037)	-0.056* (0.039)	-0.057* (0.033)	-0.058* (0.035)	-0.056** (0.038)	-0.005 (7.68)
Five Factor CAPM	-0.086*** (0.036)	-0.088*** (0.039)	-0.090* (0.039)	-0.098** (0.035)	-0.097** (0.033)	-0.011 (8.56)	-0.080** (0.031)	-0.089*** (0.031)	-0.091* (0.033)	-0.093** (0.035)	-0.010** (0.043)	0.070 (6.89)	-0.086*** (0.046)	-0.081 (0.049)	-0.098* (0.059)	-0.090* (0.025)	-0.099** (0.043)	-0.004 (8.78)
South Africa																		
One Factor CAPM	0.015** (0.011)	0.016** (0.012)	0.016* (0.011)	0.015** (0.014)	0.015*** (0.019)	0.000 (2.90)	0.011** (0.021)	0.012** (0.032)	0.011* (0.021)	0.010** (0.024)	0.009*** (0.013)	-0.002 (3.67)	0.021** (0.021)	0.022* (0.022)	0.026* (0.021)	0.019** (0.024)	0.018* (0.029)	-0.003 (6.78)
Three Factor CAPM	0.014*** (0.021)	0.014*** (0.012)	0.015*** (0.012)	0.012*** (0.013)	0.011*** (0.019)	-0.003 (0.09)	0.011*** (0.012)	0.011*** (0.011)	0.012*** (0.012)	0.010*** (0.014)	0.007*** (0.029)	-0.004 (4.67)	0.022*** (0.020)	0.024*** (0.022)	0.025*** (0.029)	0.022*** (0.023)	0.021*** (0.029)	-0.001 (5.09)
Four Factor Carhart	-0.095** (0.019)	-0.084** (0.014)	-0.080 (0.015)	-0.096* (0.018)	-0.116* (0.017)	-0.021 (5.78)	-0.092** (0.015)	-0.094** (0.015)	-0.090 (0.015)	-0.090* (0.019)	-0.101* (0.027)	-0.009 (5.78)	-0.019** (0.01)	-0.018 (0.012)	-0.090 (0.015)	-0.021* (0.015)	-0.206** (0.016)	-0.187 (8.98)
Four Factor CAPM	0.012** (0.016)	0.012** (0.014)	0.012*** (0.018)	0.010 * (0.015)	0.011** (0.017)	-0.001 (9.67)	0.032** (0.026)	0.031** (0.014)	0.032*** (0.018)	0.030 * (0.030)	0.031** (0.027)	-0.001 (8.56)	0.022** (0.026)	0.028** (0.024)	0.029*** (0.038)	0.021 * (0.025)	0.019* (0.037)	-0.003 (7.56)
Five Factor CAPM	0.012*** (0.016)	0.012*** (0.017)	0.013*** (0.014)	0.011* (0.016)	0.0103*** (0.013)	-0.0017 (9.75)	0.032*** (0.110)	0.031*** (0.111)	0.033*** (0.114)	0.031* (0.116)	0.033*** (0.113)	-0.001 (8.67)	0.022* (0.026)	0.019*** (0.037)	0.0118** (0.024)	0.021* (0.026)	0.018** (0.033)	-0.004 (8.67)

Note: The table presents the results of IR puzzle based on bivariate portfolio analysis. The full sample is divided into high, medium, and low beta firms. Then, these three groups are further divided into quintile portfolios of IR for all manufacturing firms of Pakistan and BRICS countries. Alpha is estimated using one factor to five factors CAPM models and presented along with their standard errors below in parentheses. ***, **, * shows the level of significance for 1%, 5%, and 10% respectively.

Moreover, the Carhart model does not improve the results much from the Fama-French asset pricing models. Still, investors interested in IR premiums might consider the Carhart models for Brazil, Russia, and India for better investment returns. Investors who rank their portfolios based on IR should carefully use the Carhart models with high-IR portfolios, which have more potentially abnormal returns than the Fama-French asset pricing models. Because a single factor does not describe high and significant anomalous performance in multifactor asset pricing models, a firm-specific factor is still needed to price firm-specific risk. Therefore, we add a modified mispricing factor to the five-factor Fama-French model to price this firm-specific risk or IR, and the results are shown in Table 4.10.

4.7. Determinants of Idiosyncratic Risk

To achieve third objective, in this section, we examine the empirical determinants of IR for overall firms and in different groups of firms. We first explore the link between various stock fundamentals and IR through portfolio analysis which helps find the empirical determinants of IR. Moreover, through this portfolio analysis, we can uncover several intriguing discoveries about the most prevalent and well-documented anomalies in the modern finance literature, namely the size effect and P/E ratio (price-to-earnings anomaly), and dividend anomaly. Table 4.10 shows the trend of the firm-specific variables by constructing the portfolios based on firm size and IR. The table consists of country vice five sections. Firm size portfolios are ranked by market capitalization from 1 (smallest size) to 5 (largest size).

Similarly, IR portfolios are sorted into five based on IR 1 (lowest IR) to 5 (Highest IR). After that, we applied the *t*-test to analyze whether there is a significant difference between the returns of the lowest IR and the highest IR and small size and large size ranked portfolios. Overall, the results of the *t*-test show significant differences between small and large size and low and high IR ranked portfolios across all considered countries.

By analyzing IR values based on firm size portfolios, it is observed that there is a clear pattern across all the considered countries. For instance, low-size portfolios show the highest IR values, while large-size portfolios show the lowest ones. Opposite phenomena have been observed when the values of firm size are sorted based on IR portfolios. Moreover, the mean difference test shows that there is a significant difference in firm size between the lowest IR and the highest IR ranked portfolios. The highest difference is found for South Africa, which is 3.78% and statistically significant, with a *t* value of 9.160.

The behaviour of the leverage variable exhibits a decreasing pattern moving from a small to a large portfolio. Said differently, small firms have a higher level of debt in their capital structure than their large counterparts. The opposite pattern is observed for IR portfolios that show clear increasing patterns. This implies low leverage in a low IR portfolio, which increases from the lowest to the highest. Logically, it makes sense that small firms are comparatively highly leveraged and riskier.

When observing the liquidity values, a decreasing trend has been noticed in liquidity when moving from small firm size to large size. This implies that smaller firms have larger asset turnover than their large counterpart. Conversely, no apparent pattern is observed in liquidity for IR portfolios. When moving toward the PE and DY ratios effect, an increasing pattern has been observed, suggesting that the big companies have high PE and DY ratios. In contrast, small companies have low PE and DY over the sample period. Similarly, IR portfolios also reveal the same patterns for the DY ratios, showing that low IR portfolios have the highest DY compared to the highest ones.

The values of ROE have an increasing trend moving from low to large size portfolios, showing that small firms used the equity capital in a less effective way to generate profit than large companies. Hence, the results also suggest that big companies have better management performance than small companies. This behaviour is also confirmed in the case of IR portfolios that show that low IR firms have the highest ROE and vice versa. Moving toward the market power variable, a company with market control has the right to influence the market price individually. A similar phenomenon has been observed. The large-size portfolios indicate high market power compared to the small size. Similarly, a high IR portfolio shows the lowest market power.

Overall, the results of Table 4.10 make economic sense. High IR firms have low earnings. Low earnings lead to a low earning-to-price ratio. Thus, investors are unwilling to pay a high price for such firms. Hence, it is justifiable that the values of these firms show low performance among all IR and size sorted portfolios. High leverage and low profitability also lead to increased earnings volatility over time. Volatility in earnings is a part of the firm-specific risk. Thus, companies with high leverage and low profitability tend to have high idiosyncratic volatility. The results of portfolio analysis suggest that high idiosyncratic volatility companies are small, highly leveraged, have low profitability, and investors are not willing to pay high prices for firms with a high level of IR. The findings provide insights into stylistic anomalies. There seems to be a strong proof of the size effect and IR puzzle in BRICS countries during the study period.

Table 4.10: Portfolio Analysis Sorted by Firm Size and Idiosyncratic Risk

	Based on Firm Size						Based on Idiosyncratic Risk					
Variables	1(Small Size)	2	3	4	5(Large Size)	S-L *t*-test	1(Lowest IR)	2	3	4	5(Highest IR)	L-H *t*-test
						Pakistan						
Idiosyncratic Risk	0.541	0.512	0.529	0.544	0.4217	-0.119 (3.895)						
Leverage	0.1539	0.1379	0.1276	0.1214	0.1013	-0.0526* (5.736)	0.2150	0.2531	0.2711	0.3822	0.4173	0.2023** (3.176)
Liquidity	0.1492	0.1349	0.1592	0.1977	0.1546	0.0054* (0.061)	0.1430	0.1600	0.1850	0.1190	0.1169	-0.0261* (5.125)
Momentum Return	0.0364	0.0326	0.0311	0.0348	0.0340	-0.0024 (0.65)	0.0262	0.0218	0.0175	0.0286	0.0057	-0.0205* (3.128)
Price to Earnings ratio	0.8921	0.8032	0.8110	0.8512	0.8458	-0.0463* (4.908)	0.8021	0.8482	0.8210	0.8001	0.8001	-0.0008** (4.109)
Dividend Yield	0.2258	0.2547	0.3259	0.3167	0.329	0.1032* (3.901)	0.3026	0.3271	0.3921	0.3001	0.3018	-0.0008* (1.68)
Return on Equity	-1.0125	0.6121	1.1889	1.8371	1.8289	2.8414* (2.890)	0.1903	0.0117	-0.1106	-0.0787	- 0.0823	-0.2726** (4.696)
Market Power	0.5387	0.4827	0.7756	0.1037	1.0694	0.5307* (4.564)	0.0213	0.0358	0.0370	0.0324	0.0166	-0.0047* (6.751)
Firm Size							4.152	4.1890	4.1682	4.4213	3.5254	-0.6266*** (3.064)

Variables	1(Small Size)	2	3	4	5(Large Size)	S-L t-test	1(Lowest IR)	2	3	4	5(Highest IR)	L-H t-test
Brazil												
Idiosyncratic Risk	0.0331	0.0256	0.0229	0.02344	0.0217	0.011 (1.112)						
Leverage	0.2579	0.1679	0.16662	01714	0.2013	0.056*** (2.666)	0.3550	0.1231	0.1712	0.3562	0.8073	-0.4721*** (2.556)
Liquidity	0.3492	0.6349	0.3592	0.1377	0.0846	0.264** (1.961)	0.0613	0.0600	0.0600	0.0600	0.0600	0.0013** (2.222)
Momentum Return	0.0604	0.0646	0.0603	0.06048	0.640	-0.5796*** (3.222)	2.5462	2.7818	2.7975	2.7086	2.5147	0.03156* (1.658)
Price to Earnings ratio	2.2281	2.5032	2.7110	2.8522	2.8548	-0.626*** (2.778)	2.8968	2.9912	3.2064	3.3304	2.3273	0.5695*** (3.109)
Dividend Yield	2.7358	3.4547	2.8959	3.1567	3.4049	-0.669*** (2.901)	8.932	6.9071	5.4551	3.1068	3.1998	5.7322*** (4.768)
Return on Equity	31.125	-6.821	-1.0889	-9.8371	18.4289	12.696*** (6.789)	0.9093	1.1017	1.1015	1.0787	0.78823	0.1210*** (2.896)
Market Power	0.33387	.64827	.87756	1.1037	2.0694	-1.735*** (2.998)	0.1823	0.1308	0.1310	0.1347	0.1366	0.0457* (1.875)
Firm Size							13.2860	14.5090	14.5622	14.2503	13.2654	0.0206*** (2.564)

Russia

Variables	1(Small Size)	2	3	4	5(Large Size)	S-L t-test	1(Lowest IR)	2	3	4	5(Highest IR)	L-H t-test
Idiosyncratic Risk	0.0417	0.0320	0.3031	0.02538	0.0232	0.0185*** (3.492)						
Leverage	0.1890	0.1888	0.1971	0.1517	0.1345	0.0545*** (2.669)	0.14660	0.1794	0.1779	0.1679	0.1350	0.0116*** (2.557)
Liquidity	6.4376	6.4538	6.3346	6.2262	6.1987	0.2389*** (3.457)	6.4343	6.2974	6.2217	6.2895	6.4740	-0.0397** (1.987)
Momentum Return	0 .0753	0.0134	0 .0597	0.0238	0.0238	0.0515*** (2.613)	0.0306	0.0658	0.01574	0 .0487	0.0222	0.0084*** (3.884)
Price to Earnings ratio	0.1304	0.1303	0.1303	0.1257	0.1305	0.0001	0.1285	0.1285	0.12857	0.1281	0.1280	0.0005

Variables	1(Small Size)	2	3	4	5(Large Size)	S-L t test	1(Lowest IR)	2	3	4	5(Highest IR)	L-H t-test
						(0.231)						(1.100)
Dividend Yield	2.0467	2.3078	2.2979	2.3202	2.3941	-0.3474*** (3.984)	2.4580	2.2534	2.2259	2.1737	2.1179	0.3401*** (5.765)
Return on Equity	1.6334	2.8753	1.6461	2.4791	3.2380	-1.6046*** (3.231)	19.886	16.0752	12.0823	11.2444	10.4339	9.4521*** (6.936)
Market Power	0.2574	0.3365	0.6917	1.3350	2.4223	-2.1649*** (2.300)	0.6727	1.4795	1.3433	0.94009	0.5740	0.0987*** (3.896)
Firm Size							15.5130	17.4174	17.0714	16.0629	14.9983	0.5147*** (4.234)

India

Variables	1(Small Size)	2	3	4	5(Large Size)	S-L t test	1(Lowest IR)	2	3	4	5(Highest IR)	L-H t-test
Idiosyncratic Risk	0.03731	0.0313	0.0278	0.0244	0.0232	0.0141*** (3.198)						
Leverage	0.15875	0.1571	0.1695	0.1432	0.1255	0.0332*** (2.996)	0.1452	0.1534	0.1494	0.1303	0.1454	-0.0002* (1.176)
Liquidity	3.0689	2.9116	2.5258	3.0147	3.0458	0.0231*** (3.234)	3.2530	3.2887	3.5252	3.2614	3.5173	-0.2643*** (3.543)
Momentum Return	0.0108	0.0106	0.0144	0.0140	0.0100	0.008*** (5.221)	0.0133	0.0213	0.023	0.025	0.0181	-0.0004* (1.624)
Price to Earnings ratio	0.0950	0.09480	0.0948	0.0948	0.0958	0.0008*** (5.917)	0.0936	0.0937	0.0934	0.0937	0.0934	0.0002* (1.786)
Dividend Yield	2.2962	2.4805	2.8443	3.1162	3.0768	-0.7806*** (3.901)	2.8737	2.8137	2.6742	2.6566	2.6615	0.2122*** (3.214)
Return on Equity	12.4846	16.211	20.231	14.4971	19.1171	-6.632*** (3.356)	21.78584	18.7907	15.5530	13.03003	9.93948	11.846*** (6.879)
Market Power	.16966	.36986	.5893	.9991	2.8976	2.7279*** (5.763)	1.5464	1.27042	0.88759	0.62702	0.45353	1.092*** (3.118)
Firm Size							17.4935	16.9286	16.2663	15.6974	14.9592	2.5343*** (8.231)

China

Variables	1(Small Size)	2	3	4	5(Large Size)	S-L t-test	1(Lowest IR)	2	3	4	5(Highest IR)	L-H t-test
Idiosyncratic Risk	0.02808	0.02780	0.02705	0.02674	0.0254	0.0026*** (0.5678)						
Leverage	0.2251	0.14137	0.1646	0.1982	0.1549	0.0701*** (2.918)	0.0681	0.0777	0.0766	0.0753	0.0840	-0.015*** (2.876)

Liquidity	3.32751	3.1570	3.0696	2.9474	2.8315	0.4960*** (5.437)	3.0038	3.0122	3.0252	2.9573	3.3970	-0.3932*** (4.9852)
Momentum Return	0.0748	0.06339	0.02065	0.0085	0.0008	0.074 (0.912)	0.0195	0.0195	0.0280	0.0672	0.0855	-0.066*** (2.982)
Price to Earnings ratio	0.0564	0.0565	0.0565	0.0566	0.0567	-0.0003* 1.7891	0.0566	0.0563	0.0564	0.0566	0.0562	0.0004 (0.457)
Dividend Yield	3.3533	4.0225	3.8168	3.6116	4.2270	-0.8737*** (3.000)	3.9990	3.7940	3.6351	3.5375	3.5939	0.4051*** (2.368)
Return on Equity	4.0325	7.9255	6.6582	7.7877	9.3925	-5.364*** (9.765)	.04858	.04240	.04093	.03613	.03053	0.0180** (1.915)
Market Power	0.14126	.29755	.55082	1.0361	3.0180	-2.876*** (3.453)	1.2297	1.1108	0.9638	0.8932	0.7795	0.4502*** (8.932)
Firm Size							15.4164	15.3505	15.3607	15.2756	15.2056	0.2108*** (3.914)

South Africa

Variables	1(Small Size)	2	3	4	5(Large Size)	S-L *t*-test	1(Lowest IR)	2	3	4	5(Highest IR)	L-H *t*-test
Idiosyncratic Risk	0.0607	0.0380	0.0300	0.0251	0.0229	0.0378 (9.160)						
Leverage	0.1632	0.1593	0.1418	0.1369	0.1274	0.0358** (1.918)	0.1576	0.14815	0.1531	0.1647	0.1687	-0.011 (1.399)
Liquidity	3.9049	3.6954	3.8575	3.3006	3.6140	0.2909*** (3.291)	3.5807	3.1440	3.5658	3.9883	2.3078	1.2729* (1.873)
Momentum Return	0.0060	0.0011	0.0673	0.0110	0.0119	-0.0059** (1.983)	0.0695	0.0578	0.0675	0.0636	0.0157	0.0538*** (5.2713)
Price to Earnings ratio	0.0548	0.0549	0.0550	0.0551	0.0551	-0.0003** (1.935)	0.5493	0.5489	0.5496	0.5497	0.5490	0.0039*** (6.0182)
Dividend Yield	2.1974	2.2607	2.4621	2.6527	2.6528	-0.4554*** (4.271)	2.5536	2.5845	2.5605	2.4983	2.3078	0.2458*** (3.1893)
Return on Equity	1.8139	12.583	15.1603	27.471	25.8819	-24.068*** (2.981)	4.9086	3.6132	4.1490	3.2511	3.8417	1.0669*** (2.991)
Market Power	.07736	.25018	.66433	1.1324	2.9151	-2.8377*** (3.111)	0.83526	1.28716	1.2742	0.97966	0.61027	0.2249*** (3.998)
Firm Size							13.8684	15.5963	15.2719	14.6721	12.4327	1.4357*** (3.4673)

Note: Size and IR portfolios analysis are presented. The differences between extreme portfolios are tested via *t* test. *, **, *** represents 10%, 5%, and 1% level of significance.

To find the determinants of IR for all manufacturing firms and different categories of firms, the fixed effects model is estimated separately for each BRICS member country, and regression results are shown in Table 4.11. The table consists of four panels. The first panel shows the regression results by considering all the manufacturing firms. The second, third, and fourth panels show the regression results for different categories of the firm: liquid and illiquid firms, beta-based firms, and financially constrained and financially unconstrained firms, respectively. Hausman (1978), F test, and Chi-square test indicate that fixed-effect models suit firm-specific characteristics. The values of F-statistics and adjusted R^2 also suggest that all the estimated models are well fit.

The results indicate that there is an inverse relationship between firm size and IR for all sample firms as well as for different groups of firms. This negative relationship implies that young and small firms are highly exposed to IR and vice versa. Moreover, we observe a systematic pattern in the coefficient values of firm size. For instance, the coefficient values of financially constrained, high beta, and illiquid firms are comparatively high and significant compared to their counterparts. Said differently, the exposure of IR for high beta, illiquid, and financially constrained firms is high. This evidence supports the hypothesis that firm size is negatively related to IR. The coefficient value of leverage is statistically significant, and a positive relationship is observed across all the countries considered and in different types of firms. One interesting finding observed for financially constrained firms is that the impact of leverage on IR is higher than that for financially unconstrained firms. Market power acts as a hedging mechanism that smooths the IR. As expected, a negative association has been observed between market power and IR because market power decreases information uncertainty; hence, the volatility of stock returns confirms the negative link between IR and a firm's competitiveness. Moving to the liquidity variable, we find that stock liquidity is positively and significantly related to IR for all the sample countries and types of firms. These findings suggest that high liquidity entails high IR. This implies that liquid stocks are more exposed to risk.

Arguably, the more interesting results are found for momentum returns. Consistent with the findings of McLean (2010), momentum returns do not follow a clear relationship with IR. The results indicate that some countries penalize momentum returns when IR increases. For instance, in Brazil, momentum return is significant for manufacturing firms but has no significant impact on financially unconstrained, low and medium beta, and illiquid firms. In Russia, momentum return is not significant in low beta firms. Fascinating findings have been observed for India that momentum has a weak significance for all manufacturing (with a very low magnitude of 0.001) and financially constrained firms with a magnitude of 0.095. It appears statistically significant at a 10% significance level. For the remaining types of firms, momentum is not a significant determinant of IR for India. China and South Africa show somewhat similar and very different results compared to the rest of the sampled countries. Momentum returns have a positive relationship with IR for all sample firms, including financially constrained, unconstrained, and beta-based firms. However, liquid and illiquid firms have observed a negative and significant relationship. The negative sign in liquid and illiquid firms is the short-term return reversal (Jegadeesh, 1990; Lehmann, 1990), which states that a negative relationship exists between IR and firm liquidity. Corporate investment attenuates the short-term return reversal effect by improving stock liquidity through a decrease in the firm-specific risk of a stock (Kang, Khaksari, & Nam, 2018).

A significant negative association is observed between ROE and IR for all BRICS countries except India. Kumari et al. (2017), justification for the positive sign of ROE for India is given by those who suggest lower volatility in past winner stocks. Investment decisions are more centred on past cumulative returns. The coefficient of PE is statistically significant across all firms and different categories of firms. The negative coefficient suggests that PE is negatively related to IR. This negative relationship is consistent with the findings of Firmansyah, Sihombing, and Kusumastuti (2020). PE ratio is used to calculate the valuation of firms. This implies how much an investor is willing to pay for every dollar of the company's earnings. Therefore, it is not surprising that investors are willing to pay more for companies with low IR firms but pay less for firms having more IR. The main reason for this negative relationship is the leverage effect. High-leveraged firms appear to have lower PE because debt impacts profits and equity prices. The coefficients of dividend yield are statistically significant in models 1, 2, 3, and 4, and the coefficient value varies dramatically between firm categories. For example, the coefficient values for high-beta and financially constrained firms are high and statistically significant compared to their counter companies. The table shows that dividend yield is adversely connected to idiosyncratic volatility. This implies that firms that pay regular dividends have lower IR (Liu & Di Iorio, 2012).

Overall, the results of the panel regressions suggest that leverage, liquidity, firm size, PE ratio, DY, ROE, and market power are significant determinants of IR across all manufacturing firms and in different categories of firms in all sample countries. Said differently, we reject the entire null hypothesis and accept the alternate hypothesis. Consequently, it can be declared that there is a significant relationship between idiosyncratic risks and the considered determinants of IR across all samples. Moreover, there are no considerable changes in the signs of the coefficient for different types of firms. However, the coefficient values for high-beta, financially constrained, and illiquid firms are significant and have more profound values than their counterparts for all BRICS member countries and Pakistan.

After identifying the significant determinants of IR, we check the robustness of our results in two different ways. First, we used a different model, the one-factor CAPM model, to estimate IR, and then we applied the same fixed effects model to examine the determinants of IR. The results are presented in Appendix Table A.1 Panel 1 (Model 1). We can observe through this robustness test that the results are similar in terms of signs and significance.

Our second measure of robustness check is that there is a possibility our results suffer from the problem of endogeneity. Said differently, the contemporary values of the explanatory variables may be correlated with the contemporary values of the error term.

To overcome this problem or ensure our results do not suffer from the endogeneity problem, we consider the lag values of the explanatory variables rather than their current values. The results of this exercise are presented in appendix Table A.2 Panel 2 (Model 2). As we can see from the results, both in terms of sign and significance, our results are similar to those presented earlier. The results show that firm size, market power, price-to-earnings ratio, return on equity, and dividend yield negatively impact IR, and both leverage and liquidity have a significant positive impact. However, the momentum returns have positive overall for manufacturing firms but negative and significant signs for some groups of firms. Thus, through both robustness tests, we confirm that our results are similar to the earlier findings for different methods.

Table 4.11: Determinants of Idiosyncratic Risk Overall and based on Firm Categories

Pakistan																
	Model 1		Model 2 Based on Financially Constrained (FC)				Model 3 Beta-Based Firms						Model 4 Based on Liquidity			
	All Firms		FC		FUC		Low-Beta		Medium-Beta		High-Beta		Liquid Firms		Illiquid Firms	
Variables	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
Constant	0.022***	0.027	0.012*	0.120	0.016**	0.125	0.0344*	0.054	0.035	0.0515	0.0326	0.055	0.0216	0.026	0.0219*	0.021
Firm Size	-0.004**	0.026	-0.011**	0.116	-0.056*	0.121	-0.033*	0.056	-0.031*	0.052	-0.035*	0.052	-0.067*	0.034	-0.065**	0.042
Leverage	0.013***	0.020	0.013**	0.113	0.089*	0.123	0.0831*	0.069	0.083*	0.0554	0.031**	0.071	0.037**	0.061	0.047**	0.063
Market Power	-0.014*	0.076	-0.001**	0.119	-0.019**	0.177	-0.021*	0.022	-0.023*	0.054	-0.043**	0.069	-0.038**	0.021	-0.032**	0.029
Liquidity	1.04***	0.302	0.358**	0.126	0.488**	0.099	0.0217*	0.046	0.027**	0.058	0.0254*	0.051	0.031*	0.038	0.038**	0.039
Momentum Return	0.003*	0.019	0.0019*	0.171	0.0123**	0.117	0.0217	0.036	0.028	0.061	0.0242*	0.035	-0.0215*	0.092	-0.028**	0.096
Return on Equity	-0.007**	0.013	-0.0191*	0.195	-0.0193*	0.114	-0.0418*	0.053	-0.042**	0.055	-0.0421*	0.058	-0.098**	0.024	-0.099*	0.027
Price to Earnings ratio	-0.006**	0.062	-0.0188*	0.190	-0.0198*	0.113	-0.066**	0.035	-0.064*	0.035	-0.064*	0.036	-0.074**	0.032	-0.081*	0.038
Dividend Yield	-0.0017*	0.007	-0.0127*	0.120	-0.014**	0.116	-0.0637*	0.033	-0.0626*	0.077	-0.021**	0.039	-0.061*	0.017	-0.067**	0.029
R-squared	0.145		0.149		0.147		0.150		0.151		0.142		0.137		0.126	
Number of obs	2822		1310		1512		937		1005		800		1519		1303	
F-test	8.77		28.10		32.29		14.17		55.17		54.83		59.00		18.11	
Prob > F	0.000		0.000		0.000		0.000		0.000		0.000		0.00		0.007	
Hausman Chi-square test value	103.9		128.98		125.80		119.78		120.13		130.00		210.07		218.9	
P-value	0.000		0.001		0.000		0.002		0.000		0.001		0.002		0.009	

Brazil																
	Model 1		Model 2 Based on Financially Constrained (FC)				Model 3 Beta-Based Firms						Model 4 Based on Liquidity			
	All Firms		FC		FUC		Low-Beta		Medium-Beta		High-Beta		Liquid Firms		Illiquid Firms	
Variables	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
Constant	0.029***	0.157	0.012*	0.081	0.012	0.025	0.014*	0.104	0.054	0.015	0.026	0.085	0.016	0.112	0.019*	0.016
Firm Size	-0.004*	0.056	-0.011**	0.012	-0.012*	0.021	-0.013**	0.016	-0.035*	0.012	-0.012*	0.082	-0.018***	0.084	-0.015**	0.042
Leverage	0.083***	0.020	0.021*	0.010	0.019*	0.023	0.031*	0.039	0.035*	0.014	0.028**	0.077	0.027**	0.071	0.097**	0.063
Market Power	-0.013*	0.076	-0.016**	0.010	-0.01***	0.077	-0.011**	0.012	-0.037*	0.074	-0.023**	0.064	-0.036**	0.081	-0.014**	0.032
Liquidity	0.043***	0.0132	0.018***	0.036	0.018**	0.099	0.017**	0.016	0.072**	0.048	0.0214*	0.055	0.019*	1.318	0.035**	0.033
Momentum Return	0.379*	0.019	0.019*	0.011	0.023	0.017	0.017	0.016	0.084	0.056	0.022*	0.075	-0.025	0.072	-0.021**	0.066
Return on Equity	-0.032*	0.013	-0.019**	0.015	-0.013*	0.014	-0.018*	0.083	-0.024**	0.035	-0.0221*	0.058	-0.038**	0.034	-0.019*	0.077
Price to Earnings ratio	-0.029**	0.062	-0.018*	0.012	-0.018*	0.013	-0.056**	0.085	-0.041*	0.065	-0.024**	0.026	-0.054**	0.022	-0.031*	0.088
Dividend Yield	-0.013*	0.079	-0.016*	0.036	-0.014**	0.016	-0.037*	0.043	-0.026*	0.017	-0.021**	0.046	-0.069*	0.097	-0.097**	0.069
R-squared	0.125		0.117		0.117		0.110		0.143		0.112		0.117		0.116	
Number of obs	2822		1310		1512		937		1005		800		1519		1303	
F-test	8.77		23.10		42.29		13.17		35.17		44.73		19.78		16.09	
Prob > F	0.000		0.000		0.000		0.03		0.07		0.000		0.00		0.007	
Hausman Chi-square test value	43.59		134.98		123.80		119.78		180.83		140.98		150.47		156.49	
P-value	0.000		0.000		0.000		0.000		0.000		0.001		0.002		0.009	

Russia																
	Model 1		Model 2 Based on Financially Constrained (FC)				Model 3 Beta-Based Firms						Model 4 Based on Liquidity			
	All Firms		FC		FUC		Low-Beta		Medium-Beta		High-Beta		Liquid Firms		Illiquid Firms	
Variables	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
Constant	0.028 ***	0.044	0.034*	0.02381	0.023*	0.052	0.0514*	0.041	0.015*	0.011	0.082	0.078	0.081*	0.112	0.087*	0.091
Firm Size	-0.091***	0.034	-0.019**	0.04612	-0.028**	0.022	-0.0613**	0.031	-0.013*	0.011	-0.041**	0.058	-0.088***	0.084	-0.015**	0.094
Leverage	0.031***	0.071	0.067*	0.03410	0.037*	0.032	0.0331*	0.039	0.033*	0.011	0.092**	0.037	0.028**	0.071	0.097**	0.076
Market Power	-0.012***	0.029	-0.036**	0.05310	-0.047*	0.067	-0.0511**	0.011	-0.033*	0.017	-0.032**	0.066	-0.095**	0.081	-0.038**	0.073
Liquidity	0.455*	0.268	0.087***	0.0163	0.034*	0.049	0.0617**	0.013	0.047**	0.014	0.092**	0.075	0.051**	0.318	0.073**	0.023
Momentum Return	0.038 ***	0.095	0.037*	0.0112	0.089*	0.061	0.0317	0.014	0.088*	0.015	0.052**	0.027	-0.062*	0.072	-0.051**	0.016
Return on Equity	-0.015***	0.045	-0.039**	0.0156	-0.068**	0.081	-0.061*	0.043	-0.08**	0.013	-0.062**	0.085	-0.043***	0.034	-0.081*	0.017
Price to Earnings ratio	-0.054*	0.091	-0.039*	0.0123	-0.057**	0.071	-0.0456**	0.084	-0.054*	0.016	-0.035**	0.062	-0.055**	0.022	-0.043*	0.018
Dividend Yield	-0.015*	0.083	-0.098*	0.0136	-0.089**	0.091	-0.0337*	0.044	-0.082*	0.011	-0.022**	0.054	-0.096**	0.097	-0.089**	0.0191
R-squared	0.147		0.144		0.177		0.181		0.174		0.181		0.199		0.211	
Number of obs	7500		3557		3943		1789		3113		2598		3879		3621	
F-test	18.22		27.10		32.29		18.17		55.17		34.73		19.78		26.09	
Prob > F	0.000		0.009		0.007		0.030		0.07		0.000		0.00		0.007	
Hausman Chi-square test value	11.52		64.98		83.90		116.78		128.83		137.98		93.41		55.41	
P-value	0.000		0.006		0.000		0.000		0.000		0.001		0.002		0.000	

India																
	Model 1		Model 2 Based on Financially Constrained (FC)				Model 3 Beta-Based Firms						Model 4 Based on Liquidity			
	All Firms		FC		FUC		Low-Beta		Medium-Beta		High-Beta		Liquid Firms		Illiquid Firms	
Variables	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**
Constant	0.044***	0.015	0.056*	0.087	0.023	0.125	0.034*	0.045	0.041	0.05	0.066	0.05	0.034	0.012	0.190	0.124
Firm Size	-0.027***	0.223	-0.012**	0.032	-0.058*	0.321	-0.011**	0.064	-0.033*	0.02	-0.010**	0.032	-0.018*	0.045	-0.017**	0.021
Leverage	0.014 ***	0.001	0.097*	0.081	0.025*	0.023	0.033*	0.03	0.031*	0.03	0.018*	0.067	0.055*	0.011	0.073*	0.032
Market Power	-0.163***	0.026	-0.065**	0.012	-0.067***	0.057	-0.016**	0.06	-0.034*	0.05	-0.043**	0.054	-0.038**	0.019	-0.081**	0.024
Liquidity	0.101***	0.106	0.087***	0.063	0.098**	0.089	0.067**	0.043	0.070**	0.08	0.314*	0.045	0.299*	1.318	0.058*	0.035
Momentum Return	0.001*	0.152	0.095*	0.012	0.123	0.067	0.076	0.067	0.081	0.06	0.021	0.035	-0.031	0.021	-0.013	0.065
Return on Equity	-0.041***	0.099	-0.092**	0.056	-0.023*	0.045	-0.087*	0.031	-0.043**	0.034	-0.021**	0.028	-0.011**	0.043	-0.093*	0.076
Price to Earnings ratio	-0.159***	0.188	-0.087*	0.023	-0.078*	0.036	-0.067**	0.054	-0.011*	0.05	-0.084**	0.036	-0.011**	0.027	-0.014**	0.089
Dividend Yield	-0.081***	0.011	-0.067*	0.036	-0.064**	0.067	-0.087*	0.043	-0.02*	0.014	-0.012*	0.036	-0.056*	0.074	-0.020*	0.092
R-squared	0.114		0.147		0.149		0.142		0.143		0.141		0.129		0.121	
Number of obs	8621		4310		4230		2401		2355		3865		4792		3829	
F-test	56.45		23.90		43.29		3.17		2.17		14.73		10.78		10.09	
Prob > F	0.000		0.000		0.000		0.03		0.027		0.000		0.00		0.000	
Hausman Chi-square test value	124.69		34.98		21.90		16.78		16.83		14.78		4.41		5.41	
P-value	0.000		0.000		0.000		0.000		0.000		0.000		0.000		0.000	

China

	Model 1		Model 2 Based on Financially Constrained (FC)				Model 3 Beta-Based Firms						Model 4 Based on Liquidity			
	All Firms		FC		FUC		Low-Beta		Medium-Beta		High-Beta		Liquid Firms		Illiquid Firms	
Variables	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
Constant	0.029***	0.073	0.063*	0.034	0.012*	0.086	0.084*	0.087	0.043*	0.010	0.098*	0.048	0.078*	0.101	0.098*	0.019
Firm Size	-0.076**	0.034	-0.014**	0.042	-0.024**	0.023	-0.092**	0.048	-0.036*	0.018	-0.037**	0.04	-0.008***	0.008	-0.007**	0.090
Leverage	0.002***	0.061	0.069*	0.024	0.034*	0.048	0.049**	0.083	0.063*	0.015	0.093**	0.03	0.028**	0.047	0.078**	0.034
Market Power	-0.012*	0.077	-0.056**	0.042	-0.013*	0.047	-0.023**	0.092	-0.046*	0.013	-0.018***	0.05	-0.095**	0.078	-0.038**	0.025
Liquidity	0.045***	0.071	0.027***	0.045	0.012*	0.047	0.058**	0.094	0.074**	0.013	0.099**	0.03	0.045**	0.031	0.055**	0.080
Momentum Return	0.038*	0.037	0.058*	0.025	0.023*	0.047	0.088*	0.049	0.084*	0.014	0.089**	0.09	-0.060*	0.057	-0.061**	0.061
Return on Equity	-0.015***	0.043	-0.067**	0.053	-0.025**	0.034	-0.047*	0.101	-0.068**	0.019	-0.067**	0.03	-0.033***	0.033	-0.083*	0.080
Price to Earnings ratio	-0.054*	0.029	-0.037*	0.035	-0.078**	0.067	-0.048**	0.100	-0.023*	0.012	-0.047**	0.03	-0.055**	0.052	-0.035*	0.040
Dividend Yield	-0.015 *	0.083	-0.038*	0.035	-0.098**	0.069	-0.056**	0.092	-0.083*	0.019	-0.004**	0.08	-0.016**	0.019	-0.036**	0.098
R-squared	0.147		0.164		0.169		0.191		0.1943		0.1312		0.1209		0.1201	
Number of obs	113765		53750		60015		34642		39561		39562		52476		61289	
F-test	13.28		26.10		22.29		38.17		59.17		34.73		89.78		76.09	
Prob > F	0.000		0.009		0.007		0.00		0.000		0.000		0.000		0.000	
Hausman Chi-square test value	11.52		64.98		53.90		86.78		18.83		57.98		54.41		75.41	
P-value	0.000		0.006		0.000		0.000		0.000		0.001		0.002		0.000	

South Africa

	Model 1		Model 2 Based on Financially Constrained (FC)				Model 3 Beta-Based Firms						Model 4 Based on Liquidity			
	All Firms		FC		FUC		Low-Beta		Medium-Beta		High-Beta		Liquid Firms		Illiquid Firms	
Variables	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
Constant	0.031***	0.187	0.087*	0.043	0.094*	0.054	0.043*	0.026	0.012*	0.099	0.019*	0.032	0.013*	0. 010	0.068*	0.034
Firm Size	-0.053**	0.021	-0.053**	0.014	-0.063**	0.034	-0.083**	0.082	-0.011*	0.091	-0.031**	0.026	- 0.016***	0.095	-0.006**	0.023
Leverage	0.8244**	0.409	0.033*	0.045	0.026*	0.023	0.082**	0.091	0.012*	0.021	0.019**	0.039	0.014**	0.074	0.048**	0.043
Market Power	-0.241**	0.106	-0.028**	0.034	-0.011*	0.014	-0.037**	0.089	-0.014*	0.091	-0.011***	0.045	-0.014**	0.075	-0.098**	0.078
Liquidity	0.427***	0.107	0.037***	0.034	0.081*	0.063	0.073**	0.045	0.016**	0.012	0.019**	0.075	0.012**	0.065	0.085**	0.032
Momentum Return	0.882*	0.118	0.026*	0.025	0.022*	0.034	0.067*	0.029	0.016*	0.098	0.014**	0.086	-0.034*	0.034	-0.086**	0.024
Return on Equity	-0.418***	0.188	-0.025**	0.052	-0.025**	0.012	-0.026*	0.091	-0.087**	0.067	-0.023**	0.085	- 0.012***	0.067	-0.085*	0.073
Price to Earnings ratio	-0.152 **	0.484	-0.023*	0.034	-0.018**	0.063	-0.056**	0.081	-0.081*	0.082	-0.023**	0.023	-0.016**	0.026	-0.074*	0.089
Dividend Yield	-0.016*	0.954	-0.023*	0.013	-0.018**	0.019	-0.085**	0.032	-0.026*	0.027	-0.012**	0.013	-0.023**	0.034	-0.067**	0.042
R-squared	0.125		0.106		0.105		0.102		0.109		0.109		0.112		0.129	
Number of obs	2613		1375		1238		789		1065		759		1456		1157	
F-test	70.65		56.10		42.29		98.17		89.17		44.73		69.78		56.09	
Prob > F	0.000		0.009		0.007		0.00		0.000		0.000		0.000		0.000	
Hausman Chi-square test value	35.14		34.98		33.90		36.78		38.83		37.98		34.41		35.41	
P-value	0.000		0.006		0.000		0.000		0.000		0.001		0.002		0.000	

Note: The table represents the results of panel data regression of all manufacturing firms, including financially constrained and unconstrained, high- medium- and low-beta firms, and liquid and illiquid firms. Their coefficients and standard errors are presented in the table. Hausman test is applied to select the fixed effect or random effects, estimator. Hausman test Chi-square and p-value are also given in the table. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

4.8. Pricing of Idiosyncratic Risk

After getting the evidence of the IR puzzle through parametric and non-parametric approaches, our fifth objective is to check whether IR is priced in the equity markets. In other words, this study extends the analysis in asset pricing models to examine the pricing of the possibility of a hidden non-diversifiable factor. For this, we add a modified mispricing arbitrage score factor (AS) into asset pricing models. The table presented the results from the standard one-factor CAPM model to the five-factor Fama French CAPM model. Each model includes an arbitrage score to check whether IR is priced.

Table 4.12 reports the time-series averages of the slopes, their standard errors, and adjusted R^2. The average alpha values are, in some cases, negative and positive and statistically significant from univariate to multivariate regressions implying that the predictive power of stock returns is robust to controlling for other firm characteristics and these results change little from one factor to the multi-factor asset pricing models across all sample countries.

As the main focus is the arbitrage score factor, we can observe that the arbitrage score significantly impacts the stock returns throughout the sample countries. Said differently, the arbitrage score factor is economically and statistically significant and positively affects stock returns in BRICS' equity markets. These results support using the arbitrage score as a proxy for relative stock mispricing. These results confirm that the CAPM probably leaves out non-diversifiable factor(s) in its specification, and similarly, the same issue is observed for using the Fama-French models. Therefore, it is advisable to proclaim the inclusion of IR in asset pricing models.

Table 4.12: Identifying Idiosyncratic Risk Puzzle in Asset Pricing Framework

	(1)	(2)	(3)	(4)	(5)
			Pakistan		
Alpha	2.674***	-2.395***	2.4949***	-0.1823***	-0.1688***
	(0.211)	(0.201)	0.808	0.920	0.120
Market Return	0.2319***	0.0516***	0.0009	0.0228***	0.0424***
	(0.102)	(0.211)	0.342	0.760	0.231
SMB		1.2598***	-0.9761***	-0.8613***	-0.6493***
		(0.127)	0.891	0.461	0.618
HML		1.0387***	0.7686***	0.9687***	0.9608***
		(0.919)	0.672	0.272	0.276
UMD			0.1395***		
			0.826		
RMW				-0.9324***	-0.9758***
				0.146	0.232
CMA					0.4867***
					0.011
Arbitrage Score	0.0014*	0.0119**	0.0139**	0.0144*	0.0174***
	0.028	0.0189	0.0188	0.0108	0.0148
Arbitrage					
Adj. R^2	0.0344	0.4300	0.4101	0.4628	0.4701
P-value of F-statistics	0.000	0.000	0.000	0.000	0.000
			Brazil		
Alpha	-0.0962***	-0.0914***	0.06829***	-0.0796***	-0.0819***
	(0.0215)	(0.0216)	(0.0173)	(0.0241)	(0.025)
Market Return	0.0119**	0.0101***	0.0690***	0.0782***	0.0782***
	(0.0669)	(0.0613)	(0.0528)	(0.0549)	(0.0549)
SMB		0.0507***	-0.14291***	0.3951***	0.2519***
		(0.0190)	(0.0165)	(0.0174)	(0.0172)
HML		1.4295***	0.7577***	1.6131***	1.5448***
		(0.0213)	(0.1976)	(0.1910)	(0.193)
MOM			-0.2220***		
			(0.2922)		
RMW				-0.8013***	-0.8319***
				(0.020)	(0.024)
CMA					-0.8892***
					(0.0243)
Arbitrage Score	0.0175**	0.0115**	0.0260***	0.0381**	0.0211**
	(0.008)	(0.018)	(0.0061)	(0.0065)	(0.0105
Adj. R^2	0.0128	0.1743	0.3883	0.3391	0.3394
F-test	162.24	130.04	131..05	25.26	21.51
P-value of F-statistics	0.000	0.000	0.000	0.000	0.000
			Russia		
Alpha	-0.0918 ***	-0.0115 ***	0.1733***	0.03725***	0.0366 ***
	(0.0105)	(0.011)	(0.423)	(0.0944)	(0.011)
Market Return	0.4540***	0.4756 ***	0.4717**	0.4047 ***	0.4540***
	(0.0062)	(0.063)	(0.0611)	(0.0491)	(0.057)

SMB		0.0759***	0.2124***	0.3743***	0.4140**
		(0.156)	(0.015)	(0.012)	(0.0129)
HML		-0.1852***	-0.3249***	-0.3352***	-0.1985***
		(0.114)	(0.0113)	(0.912)	(0.010)
MOM			-0.0145***		
			(0.0322)		
RMW				-0.4785***	-0.4505***
				(0.388)	(0.042)
CMA					0.1021***
					(0.036)
Arbitrage Score	0.3878**	0.2116**	0.0311**	0.0248**	0.0147***
	(0.0864)	(0.114)	(0.011)	(0.0886)	(0.168)
Adj. R^2	0.1633	0.1758	0.2344	0.5116	0.5120
F-statistics	1226.00	1905.50	2050.45	5612.53	3902.02
P-value	0.000	0.000	0.000	0.000	0.000

			India		
Alpha	-0.0529***	-0.0506***	0.0589***	-0.0567***	-0.057***
	(0.076)	(0.609)	(0.0831)	(0.081)	(0.080)
Market Return	0.0328***	0.0653***	0.0752***	0.0736***	0.0166***
	(0.015)	(0.012)	(0.113)	(0.111)	(0.127)
SMB		0.7300***	0.741***	0.8105***	1.8211***
		(0.061)	(0.057)	(0.581)	(0.835)
HML		0.4225***	0.3276***	2.9609***	1.2919***
		(0.086)	(0.081)	(0.80)	(0.963)
MOM			-0.0853***	-0.0833***	-0.1099***
			(0.088)	(0.874)	(0.084)
RMW				-2.154***	-0.0782***
				0.0481	(0.045)
CMA					1.8466**
					(0.010)
Arbitrage Score	0.416***	0.5466***	1.2566***	0.666***	0.0786**
	(0.1720)	(0.1360)	(0.1270)	(0.1330)	(0.043)
Adj. R^2	0.077	0.3929	0.4760	0.4944	0.6293
F-test	453.15	12544.50	13206.05	11371.70	111.90
P-value of F-statistics	0.000	0.000	0.000	0.000	0.000

			China		
Alpha	-0.1910***	-0.1012***	-0.0156***	-0.0196***	-0.1190***
	(0.1909)	(0.043)	(0.0133)	(0.0151)	(0.164)
Market Return	0.1381**	0.1055***	0.1134***	0.1184***	0.1004***
	(0.1201)	(0.1021)	(0.116)	(0.106)	(0.1020)
SMB		-0.1198***	-0.2108***	0.1512***	0.1572***
		(0.0901)	(0.0404)	(0.034)	(0.042)
HML		0.6486***	0.6462***	0.6131***	0.6109***
		(0.0448)	(0.0418)	(1.040)	(0.051)
MOM			-0.255***		
			(0.0503)		
RMW				-0.1013***	-0.1319***
				(0.120)	(0.124)
CMA					-0.0347**
					(0.163)

Arbitrage Score	0.0198*	0.0218**	0.0201**	0.0298**	0.0309**
	(0.068)	(0.018)	(0.145)	(0.198)	(0.168)
Adj. R^2	0.0228	0.1703	0.1917	0.3343	0.409
F-test	160.19	91.049	192..05	79.26	60.51
P-value of F-statistics	0.009	0.001	0.000	0.001	0.011
Observations	58,153	58,153	58,153	58,153	58,153

			South Africa		
Alpha	0.0017***	0.0013***	-0.0079***	0.0073***	0.0012***
	(0.0005)	(0.001)	(0.004)	(0.003)	(0.004)
Market Return	0.0179***	0.0240***	0.0207***	0.0217 ***	0.0218 ***
	(0.045)	(0.003)	(0.004)	(0.006)	(0.003)
SMB		-0.0051***	-0.0061***	0.0062***	0.0049***
		(0.009)	(0.009)	(0.008)	(0.005)
HML		-0.0478***	-0.0363**	-0.0347***	-0.0383***
		(0.007)	(0.003)	(0.002)	(0.0012)
MOM			0.0168***		
			(0.003)		
RMW				-0.0057***	-0.0097***
				(0.004)	(0.034)
CMA					0.0093***
					(0.013)
Arbitrage Score	0.0832*	0.0712**	0.0612**	0.0512**	0.0537
	(0.6230)	(0.5230)	(0.4120)	(0.4020)	(0.405)
Adj. R^2	0.0383	0.13797	0.14934	0.15512	0.14828
F-statistics	1557.40	2082.56	1713.15	433.21	946.89
P-value	0.000	0.000	0.000	0.000	0.000

Note: In this table, pricing of idiosyncratic risk is done by adding a modified arbitrage score factor into the asset pricing model. The standard errors are presented in parentheses. *** p<1%, ** p<5%, * p<10% shows the significance levels.

4.9. Idiosyncratic Tail Risk Puzzle

By considering the sixth objective, we examine the relationship of ITR and stock returns in the upper and lower tail of ITR by running the quintile regressions (QR) at 20%, 40%, 60%, and 80% and also ordinary least squares for comparison with quintile regressions results. Table 4.13 Part A shows the QR model results displaying how the ITR relationship is associated with the stock returns. Considering equation 3.17, this study runs the quintile regression of stock returns on ITR and other control variables, namely, return reversal, momentum returns, market-to-book ratio, downside co-skewness, and firm beta, using monthly frequency data.

Overall, we can observe that the coefficient values of the ITR have consistently negative signs and tend to decrease with the increase in the quintile of stock returns. In other words, the coefficient values of ITR from the low to high quintile of stock returns tend to decrease monotonically. Thus, we can conclude that through quintile regression, we find "idiosyncratic tail risk puzzle" or a negative effect of idiosyncratic tail risk toward stock return in all BRICS, including the Pakistani equity market. These results are consistent with (Atilgan, Bali, Demirtas, & Gunaydin, 2020). It means that after controlling risk factors such as downside co-skewness, systematic risk, and market-to-book ratio, the ITR has a significant negative relationship with stock return. Simultaneously other risk factors, such as systematic risk and downside co-skewness, are negatively associated with the stock returns across all BRICS countries and Pakistan.

According to theory, the remaining core variables' coefficients are highly significant at any acceptable level of significance. The results of the QR model show changes from 20% to 80%, and the QR estimates of the IR coefficient vary in magnitude and decrease with an increase in the stock returns quintile. However, the coefficient value using the OLS estimate of ITR is positive and significant for Russia. For instance, Russia is the only country where the coefficient of ITR is observed.

The remaining sample countries found IR puzzle from 20% to 80% quantiles. The same results are for all sample countries; the only difference exists in the intensity across quantiles of the relationship between ITR and stock returns. One interesting thing we observed is that in the 20% or lowest quantile, the magnitude of this negative relationship is large for China and India compared to their counterpart countries.

However, although for 80% quantile, the magnitude for Pakistan, Brazil and South Africa is not large but has a significant effect. The results show that ITR has a statistically negative coefficient for all sample countries, showing that the ITR puzzle exists in all emerging and Pakistani equity markets. These findings are consistent with (Long et al., 2018). However, our results contradict (Long et al., 2019). They found that the ITR puzzle exists in the developed equity market, and no evidence is found of ITR for emerging markets. However, they used the index data for developed, developing and emerging equity markets rather than firm-level. The OLS estimates show that IR coefficients are negative and significant at any acceptable significance level for all BRICS except Russia including Pakistan.

The relationship between stock returns and upper tail risk is shown in Table 4.13 Part B. The findings show that upper tail risk has a significant positive impact on stock returns for 60% to 80% and OLS estimates for all sample countries except India and China, as the coefficient values of upper tail risk are consistently positive across all quantiles.

Turning to the coefficient values of systematic risk, the signs change from negative to positive, moving from 20% to 80%. These results are consistent with Glenn, Pettengill, and Mathur (1995) that positive signs, as predicted by the Sharpe-Lintner-Black model based on expected and when stock returns performance are low, for instance, there is a negative relationship is observed between market risk and stock returns. The rationale for this negative association is stated by Qadan et al. (2019) that due to the limits of arbitrage, it discourages the investors from correcting potential mispricing and leads to lower future returns. Therefore, for in-depth analysis, we further investigate the existence of ITR in different groups of firms.

Table 4.13: Identifying Idiosyncratic Tail Risk Puzzle Through Quintile Regression

Part A Extreme Negative Tail Distribution (Lower tail)

Variables	20%	40%	60%	80%	OLS
Pakistan					
Constant					0.1101*
					(0.110)
Idiosyncratic Tail Risk	-0.0117**	-0.2042**	-0.2174*	-0.3189**	-0.294**
	(0.113)	(0.113)	(0.114)	(0.113)	(0.183)
Return Reversal	0.1037*	0.1043**	0.1105**	0.1510**	0.1083***
	(0.127)	(0.112)	(0.138)	(0.116)	(0.119)
Momentum Returns	-0.1970**	0.0171**	0.1027**	0.1219*	0.1812**
	(0.136)	(0.192)	(0.199)	(0.184)	(0.178)
Market to Book Ratio	0.0396*	0.0318*	0.0372*	0.0328*	0.0392*
	(0.207)	(0.218)	(0.302)	(0.208)	(0.309)
Downside Coskewness	-0.0211*	-0.0291***	-0.0289***	-0.0272*	-0.0258*
	(0.119)	(0.131)	(0.179)	(0.121)	(0.181)
Systematic Risk	-0.1223*	-0.1542**	-0.1081***	0.1052*	0.1084*
	(0.417)	(0.419)	(0.405)	(0.407)	(0.401)
Brazil					
Constant					0.0501*
					(0.010)
Idiosyncratic Tail Risk	-0.0217**	-0.2167*	-0.2082**	-0.2919**	-0.2990**
	(0.043)	(0.063)	(0.024)	(0.043)	(0.043)
Return Reversal	0.0537*	0.0591*	0.0481*	0.0492**	0.0353*
	(0.117)	(0.107)	(0.167)	(0.126)	(0.182)
Momentum Returns	-0.2180**	-0.2089*	-0.2198*	-0.283*	-0.2431**
	(0.186)	(0.121)	(0.116)	(0.182)	(0.192)
Market to Book Ratio	0.196*	0.991**	0.891*	0.319**	0.912*
	(0.178)	(0.170)	(0.932)	(0.178)	(0.216)
Downside Coskewness	-0.0331*	-0.0411**	-0.0142*	-0.142**	-0.432**
	(0.119)	(0.210)	(0.289)	(0.242)	(0.242)
Systematic Risk	-0.0227**	0.0267**	0.0284*	0.0287*	0.0256*
	(0.284)	(0.289)	(0.218)	(0.268)	(0.278)
Russia					
Constant					0.0238**
					(0.116)
Idiosyncratic Tail Risk	-0.0616***	-0.0616***	-0.0616***	-0.0619***	0.0346**
	(0.142)	(0.133)	(0.189)	(0.178)	(0.577)
Return Reversal	0.1067***	0.1182***	0.1189**	0.1129**	0.01389***
	(0.023)	(0.0207)	(0.0207)	(0.0270)	(0.0372)
Momentum Returns	-0.07731***	-0.0672**	-0.0424*	-0.0734**	-0.0483**
	(0.017)	(0.018)	(0.017)	(0.018)	(0.02)
Market to Book Ratio	0.1341***	0.1881***	0.1821*	0.1731**	0.1673***
	(0.072)	(0.012)	(0.016)	(0.017)	(0.0384)
Downside Coskewness	-0.0210***	-0.0267	-0.0281*	-0.0298**	-0.0317***
	(0.030)	(0.018)	(0.067)	(0.071)	(0.0278)
Systematic Risk	-0.0537**	0.0587**	0.0594*	0.0527*	0.0586*

	(0.194)	(0.189)	(0.118)	(0.138)	(0.167)
India					
Constant					0.2897*
					(0.171)
Idiosyncratic Tail Risk	-0.3902*	-0.2923*	-0.2692**	-0.3989**	-0.1123**
	(0.182)	(0.162)	(0.382)	(0.328)	(0.196)
Return Reversal	0.1291*	0.1293*	0.1892*	0.1882*	0.1167*
	(0.1072)	(0.1783)	(0.1892)	(0.1832)	(0.113)
Momentum Returns	0.0400*	0.0451*	0.0523*	0.0722*	-0.0573*
	(0.102)	(0.103)	(0.178)	(0.167)	(0.360)
Market to Book Ratio	0.1126*	0.1160*	0.1178*	0.1139*	0.1792*
	(0.172)	(0.199)	(0.178)	(0.183)	(0.138)
Downside Coskewness	-0.0192*	-0.0192*	-0.3182*	-0.271*	-0.1192**
	(0.189)	(0.189)	(0.178)	(0.317)	(0.1189)
Systematic Risk	-0.5017**	0.5089**	0.5091*	0.5027*	0.5072*
	(0.0914)	(0.089)	(0.078)	(0.088)	(0.107)
China					
Constant					0.0617*
					(0.230)
Idiosyncratic Tail Risk	-0.1014***	-0.1478***	-0.1637*	-0.1927**	-0.7014***
	(0.153)	(0.1289)	(0.126)	(0.261)	(0.1053)
Return Reversal	0.2103***	0.2893***	0.2713*	0.2782*	0.2203***
	(0.189)	(0.167)	(0.271)	(0.282)	(0.1109)
Momentum Returns	0.3112**	0.3728*	0.2718*	0.2782*	0.3812**
	(0.189)	(0.179)	(0.172)	(0.184)	(0.178)
Market to Book Ratio	0.1692**	0.1228**	0.1372*	0.183*	0.0692**
	(0.1390)	(0.190)	(0.193)	(0.184)	(0.3290)
Downside Coskewness	-0.1198*	-0.1292*	-0.1282	-0.1839**	-0.0118*
	(0.181)	(0.192)	(0.182)	(0.189)	(0.112)
Systematic Risk	-0.4175**	0.4919**	0.4591*	0.5897*	0.5422*
	(0.114)	(0.149)	(0.198)	(0.188)	(0.191)
South Africa					
Constant					0.0562*
					(0.0167)
Idiosyncratic Tail Risk	-0.0578*	-0.0612*	-0.0782**	-0.0767*	-0.682*
	(0.172)	(0.189)	(0.157)	(0.672)	(0.267)
Return Reversal	0.0279*	0.0282**	0.0273*	0.3526**	0.2734**
	(0.173)	(0.183)	(0.178)	(0.268)	(0.271)
Momentum Returns	0.7293**	0.6942*	0.4841*	0.8274*	0.4262*
	(0.184)	(0.294)	(0.218)	(0.256)	(0.327)
Market to Book Ratio	0.2861*	0.2814**	0.2989**	0.2894*	0.2893**
	(0.279)	(0.281)	(0.289)	(0.248)	(0.582)
Downside Coskewness	-0.2842*	-0.4251*	-0.2792**	-0.279**	-0.2844*
	(0.125)	(0.174)	(0.167)	(0.184)	(0.183)
Systematic Risk	-0.0678**	0.0919**	0.0709*	0.0897*	0.0822*
	(0.103)	(0.199)	(0.198)	(0.118)	(0.124)

Note: The table presents the relationship between idiosyncratic tail risk (negative tail/lower tail) and returns for BRICS and Pakistan. The coefficients and in parathesis standard errors are presented in the table. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively

In sum, using quantile regression, this table shows the results to examine the return predictability of time-varying extreme upper tail risk at the different points on the return distribution. We find evidence of a strong predictive negative relationship at the lower quantiles of stock returns. However, our results show no negative association between tail risk and stock returns at the higher quantiles. Taken together, the evidence explains the abnormally large negative equity premium observed for lower quantiles of stock returns.

To examine the ITR puzzle in different groups of firms, we have divided firms into various groups to achieve the 8^{th} objective of this study. The results of the ITR puzzle for liquid and illiquid firms are displayed in Table 4.14. Univariate time series analysis was done using several steps: All companies were sorted and divided into five portfolios (quintile portfolio) based on ITR. After that, a sixth portfolio was made: the difference in return between the high and low idiosyncratic tail risk portfolios. Later, the alpha one- to five-factor CAPM models and the Carhart model were calculated from the portfolio that had been divided. This same procedure is done for both liquid and illiquid firms.

The alpha values (abnormal return performance) are listed in the table, along with their standard errors in parentheses. We list the t statistics in the IR5-IR1 column to demonstrate the variance in alpha values between the groups of firms. This column is added to assess whether there is a substantial difference between the extreme portfolios in alpha values and GRS t statistics. Overall, the alpha values of ITR of sample countries are negative and significant for the sample firms.

Specifically, we observe compare the alpha values for liquid and illiquid firms interestingly, one common finding that all sampled countries is more and less the negative alpha (abnormal return performance) for the highest portfolios named ITR5 are low compared to the lowest ITR1 portfolios for all CAPM models. However, Carhart models show positive alpha values for Brazil, Russia, and India. Moreover, the abnormal return performance for the one-factor CAPM model shows significant positive performance for both types of firms in Pakistan.

Further, when we compare the relationship between ITR and stock returns based on liquid and illiquid firms, we can conclude that illiquid firms group is more exposed due to the high level of ITR. Said differently, when both types of liquid and illiquid firms are considered, illiquid type does considerably have high exposure due to ITR than the other liquid type. In constrast, in India the intensity of ITR puzzle existence in liquid firms high than illiquid firms. The finding for China and South Africa show somewhat similar results that illiquid firms are more exposed to ITR puzzle in one-factor, three-factors, four-factors CAPM models.

In sum, we find that the ITR puzzle is found in both liquid and illiquid firms. However, the intensity of ITR puzzle in illiquid firms are high than liquid firms. This implies that there is a statistically negative relationship between ITR and stock returns of BRICS countries and Pakistan firms.

We contend that financial stability acts as a 'vaccine' for the tail risk during financial crises. So to examine the ITR puzzle in FC and FUC firms is also included in our objective of this study. Table 4.15 reports the results of the ITR puzzle for FC and FUC. The table reports the alpha values of the CAPM, the one- to the five-factor CAPM, and the Carhart model estimated based on the first sorting criteria of financial constrained. Then this sorting is further divided into quintile-based portfolios of ITR. The table shows only the alpha and their standard deviations. FC firms should theoretically provide lower returns than FUC firms. According to this intuition, investors should receive rewards for holding stocks whose returns improve, as financial limitations do so if they are severe. In all CAPM models, the difference between ITR5 and ITR1 is very substantial. Therefore, regardless of the asset pricing models used, the GRS test strongly rejects the null hypothesis that alphas are zero. In other words, it is proof of the ITR dilemma. Overall, we find the ITR puzzle for both types (FU and FUC) firms.

Specifically, the results for Pakistan show that the exposure (negative alpha values) or the negative effect of ITR is more intense for the FUC group for all the CAPM and Carhart models except the one-factor CAPM model. When we discuss the exposure of ITR in emerging countries, we cannot see a clear pattern of which group is more affected. However, we can say that the intensity of ITR puzzle is mostly high in the FUC group of firms while considering the alpha values of ITR5 portfolios. Said differently, abnormal performance (alpha) is the lowest in ITR5 portfolios in the BRICS countries mostly. Notably, the alpha values for ITR5 in Brazil, show that the evident of the ITR puzzle in all CAPM models except in three-factor CAPM. For Russia, there is also a strong tendency of existence of ITR puzzle in all CAPM models except in four-factor Carhart model.

To examine the sensitivity of the ITR puzzle based on market risk, we divide the firms into three groups (low-, medium-, and high-beta firms) and estimate the alpha values using asset pricing models. The estimated alpha values and their standard errors are presented in Table 4.16. Any efficient asset pricing model must be able to capture all alpha values that should be zero. However, the table shows the non-zero alpha values irrespective of the beta-based group of firms. Overall, there are mix findings for the favor of ITR puzzle in beta-based groups of firms. However, there is not indication of the ITR puzzle in using one-factor CAPM for Pakistan and South Africa case and in four-carhart model for Brazil, Russia, and India.

The findings of remaining CAPM models show that there are mix findings in favor of ITR puzzle in sample countries. For instance, the findings of Pakistan, Brazil, and India show that the ITR puzzle is more stressful for high-beta firms than their counterparts for some CAPM models. As we can observe, the alpha values of ITR5 for high-beta firms show worse performance in terms of returns. This implies that high-beta firms institutively are the risky firms, that is why their returns relationship with their ITR is also worse as increase the ITR. Similary, in some CAPM models the intensity of ITR puzzle in low-beta firms are high.

Part B: Extreme Positive Tail Distribution (Upper Tail)					
			Pakistan		
	Quantiles				
Variables	**20%**	**40%**	**60%**	**80%**	**OLS**
Constant					0.1001*
					(0.210)
Idiosyncratic Tail Risk	-0.1017***	-0.3012***	0.1172**	0.2199**	0.194**
	(0.113)	(0.103)	(0.214)	(0.013)	(0.283)
Return Reversal	0.3130*	0.2013**	0.2102**	0.3511**	0.2082***
	(0.107)	(0.212)	(0.103)	(0.115)	(0.129)
Momentum Returns	0.1920*	0.1070*	0.1122***	0.2212**	0.1612***
	(0.126)	(0.194)	(0.299)	(0.164)	(0.190)
Market to Book Ratio	0.0316**	0.1318**	0.0172**	0.1322**	0.0192**
	(0.207)	(0.218)	(0.102)	(0.508)	(0.402)
Downside Coskewness	-0.0310**	-0.1201***	-0.3219*	-0.1172**	-0.1268**
	(0.119)	(0.131)	(0.179)	(0.121)	(0.181)
Systematic Risk	-0.1223**	-0.2542***	0.1081*	0.1452**	0.1034***
	(0.407)	(0.423)	(0.209)	(0.307)	(0.301)
			Brazil		
Constant					0.1501**
					(1.111)
Idiosyncratic Tail Risk	-0.0207*	-0.2067**	0.2180**	0.3909*	0.1991**
	(0.142)	(0.262)	(0.122)	(0.241)	(0.230)
Return Reversal	0.1526*	0.3590***	0.1421***	0.3491***	0.1352**
	(0.107)	(0.127)	(0.307)	(0.025)	(0.281)
Momentum Returns	0.1180*	0.2081**	0.1190**	0.4811**	0.5430*
	(0.136)	(0.101)	(0.113)	(0.283)	(0.198)
Market to Book Ratio	0.296**	0.390***	0.391**	0.309*	0.913**
	(0.372)	(0.143)	(0.937)	(0.574)	(0.210)
Downside Coskewness	-0.1331**	-0.2410*	-0.3143**	-0.1414*	-0.431*
	(0.110)	(0.211)	(0.189)	(0.232)	(0.202)
Systematic Risk	-0.0123**	-0.0142***	0.0011*	0.0152**	0.0134***
	(0.017)	(0.023)	(0.039)	(0.017)	(0.0201)
			Russia		
Constant					0.1132*
					(0.216)
Idiosyncratic Tail Risk	-0.0116**	-0.2606***	0.1606*	0.1316***	0.1336*
	(0.142)	(0.133)	(0.189)	(0.178)	(0.577)
Return Reversal	0.1107**	0.1081**	0.1089*	0.2129***	0.1189*
	(0.123)	(0.2204)	(0.1203)	(0.0470)	(0.0571)
Momentum Returns	0.17730*	0.0372*	0.0224**	0.0734***	0.0470*
	(0.017)	(0.018)	(0.017)	(0.018)	(0.02)
Market to Book Ratio	0.3340***	0.3881***	0.1521*	0.19831**	0.1679***
	(0.072)	(0.012)	(0.016)	(0.017)	(0.0384)
Downside Coskewness	-0.0411***	-0.0367*	-0.0401**	-0.1290**	-0.0118*
	(0.031)	(0.118)	(0.267)	(0.370)	(01277)
Systematic Risk	-0.015***	0.0167*	0.0171**	0.0190**	0.0158*
	(0.031)	(0.118)	(0.267)	(0.370)	(01277)
			India		
Constant					0.2521**
					(0.110)
Idiosyncratic Tail Risk	0.1201*	0.2161**	0.1082**	0.2902**	0.191**
	(0.241)	(0.262)	(0.123)	(0.043)	(0.413)
Return Reversal	0.0137**	0.1591*	0.0380*	0.0392*	0.0320**
	(0.107)	(0.120)	(0.131)	(0.026)	(0.183)

Momentum Returns	0.2081**	0.3084**	0.5190*	0.183*	0.2331**
	(0.286)	(0.141)	(0.312)	(0.281)	(0.391)
Market to Book Ratio	0.120***	0.931***	0.492**	0.415*	0.412**
	(0.108)	(0.172)	(0.932)	(0.170)	(0.416)
Downside Coskewness	0.1330*	0.3410*	0.4142*	0.242*	0.332**
	(0.219)	(0.310)	(0.589)	(0.202)	(0.941)
Systematic Risk	0.1781**	0.1371*	0.1511**	0.1890**	0.148*
	(0.201)	(0.208)	(0.207)	(0.370)	(01277)
China					
Constant					0.1222*
					(0.110)
Idiosyncratic Tail Risk	0.0616*	0.0616*	0.0616*	0.0616**	0.0346*
	(0.142)	(0.133)	(0.109)	(0.128)	(0.537)
Return Reversal	0.1367*	0.1180*	0.2180**	0.1329*	0.0385**
	(0.023)	(0.0207)	(0.0207)	(0.0270)	(0.0372)
Momentum Returns	0.07731***	0.1672**	0.2424*	0.4734**	0.3483**
	(0.117)	(0.038)	(0.017)	(0.018)	(0.12)
Market to Book Ratio	0.1241***	0.1381***	0.1421*	0.3731**	0.4673*
	(0.272)	(0.212)	(0.416)	(0.817)	(0.0384)
Downside Coskewness	0.0210***	0.2267	0.3281*	0.1298**	0.0317**
	(0.330)	(0.318)	(0.367)	(0.071)	(0.0478)
Systematic Risk	0.081**	0.0531*	0.0741**	0.0834*	0.054*
	(0.311)	(0.318)	(0.217)	(0.245)	(0.213)
South Africa					
Constant					0.2101*
					(0.410)
Idiosyncratic Tail Risk	-0.2117*	-0.4042***	0.1117*	0.3042*	0.3117*
	(0.103)	(0.123)	(0.013)	(0.213)	(0.134)
Return Reversal	0.1237*	0.1543*	0.2037*	0.1543**	0.4037*
	(0.127)	(0.112)	(0.127)	(0.112)	(0.127)
Momentum Returns	0.1473**	0.0171*	0.0970*	0.0171**	0.0970**
	(0.136)	(0.182)	(0.136)	(0.292)	(0.126)
Market to Book Ratio	0.0296**	0.0118**	0.0196***	0.1318*	0.1396*
	(0.207)	(0.218)	(0.207)	(1.218)	(0.207)
Downside Coskewness	-0.0211**	-0.0271*	-0.0211**	-0.1291**	-0.1211*
	(0.019)	(0.131)	(0.109)	(0.131)	(0.319)
Systematic Risk	-0.242**	-0.211*	0.2911**	0.3411**	0.325*
	(0.134)	(0.101)	(0.139)	(0.151)	(0.119)

Note: The table presents the relationship between idiosyncratic tail risk and returns for BRICS and Pakistan. The coefficients and in parathesis standard errors are presented in the table. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Table 4.14: Idiosyncratic Tail Risk Puzzle in Liquid and Illiquid Firms

Portfolios / Models	Liquid Firms						Illiquid Firms					
	ITR1	ITR2	ITR3	ITR4	ITR5	ITR5-ITR1	ITR1	ITR2	ITR3	ITR4	ITR5	ITR5-ITR1
Pakistan												
One-Factor CAPM	0.5217*** (0.355)	0.5141* (0.331)	0.5132* (0 362)	0.5111 (0.352)	0.5015* (0.318)	-0.020** (4.218)	0.5572*** (0.121)	0.5578*** (0.129)	0.5571*** (0.128)	0.5574*** (0.125)	0.5571*** (0.025)	-0 0001* (1.783)
Three-Factor CAPM	-0.2054*** (0.239)	-0.2211* (0 262)	-0.2231* (0.272)	-0.2021* (0.295)	-0.2315 (0.376)	-0.026** (3.902)	-0.2064*** (0 421)	-0.2062*** (0.422)	-0.2066*** (0.426)	-0.2068*** (0.429)	-0.3064** (0.521)	-0.5128*** (8 953)
Four-Factor Carhart	-0 1098*** (0.422)	-0.1291*** (0.423)	-0.1391** (0.433)	-0 1191*** (0.443)	-0 1692** (0.411)	0.059** (3.092)	-0.8764*** (0.502)	-0.8761*** (0.509)	-0.8768*** (0.504)	-0.8769*** (0.503)	-0.8772*** (0.602)	-1.7533*** (9.453)
Four-Factor CAPM	-1.2103*** (0.253)	-1.2203*** (0.243)	-1.2301*** (0 233)	-1.2104*** (0.243)	-1.2106*** (0 263)	0.000* (2.562)	-1 8281*** (0.351)	-1.8280*** (0.352)	-1 8285*** (0.354)	-1.8286*** (0.358)	-1.9281*** (0.451)	-3.7562*** (13.965)
Five-Factor CAPM	-1 1371*** (0.551)	-1.1157*** (0.552)	-1 1250*** (0.552)	-1.1251*** (0.551)	-1.1151*** (0.554)	-2.252*** (6.829)	-1.2333*** (0.656)	-1.2330*** (0.651)	-1.2334*** (0 652)	-1.2336*** (0 657)	-1.3338*** (0.757)	-2.5671*** (7.946)
Brazil												
One-Factor CAPM	-0.8132*** (0.327)	-0.8131*** (0.322)	-0.8134*** (0.325)	-0.8137*** (0.328)	-0.8139*** (0.323)	-1.627** (4.785)	-0.7140*** (0 221)	-0.7142*** (0.224)	-0.7148*** (0.229)	-0.7146*** (0.225)	-0.8149*** (0.328)	-1.5289* (0.573)
Three-Factor CAPM	-0.6156*** (0.411)	-0.6151*** (0.413)	-0.6152*** (0.416)	-0.6155*** (0.418)	-0.6158*** (0.417)	-1.231*** (4.968)	-0.2270*** (0.134)	-0.2271*** (0.131)	-0.2274*** (0.135)	-0.2276*** (0.138)	-0.3279*** (0.239)	-0.5549*** (3.967)
Four-Factor Carhart	0.9625* (0.291)	0.9621* (0 294)	0.9627* (0.296)	0.9628* (0 298)	0.9609* (0.299)	-0.001* (2.903)	1.3066*** (0 403)	1.3060*** (0.401)	1.3068*** (0.404)	1.3061*** (0.409)	1.2066*** (0.303)	-0.1000* (0.294)
Four-Factor CAPM	-0 8880 (0.676)	-0.8882** (0.633)	-0.8883** (0.677)	-0.8885** (0.678)	-0.8889* (0.679)	-1.776** (1.295)	-0.7077*** (0.214)	-0.7078*** (0.213)	-0 7071*** (0.212)	-0.7078*** (0.211)	-0 8077*** (0.313)	-1.5154*** (5.685)
Five-Factor CAPM	-0.7481* (0.239)	-0.7882* (0.276)	-0.7880** (0.279)	-0.7886* (0.277)	-0.7884** (0 274)	-1.536** (6.639)	-0.3107*** (0.113)	-0.3108*** (0.110)	-0.3108*** (0 114)	-0.3109*** (0.115)	-0.417*** (0.216)	-0.7277*** (4.9573)
Russia												
One-Factor CAPM	0.1406** (0.406)	0.1410** (0.409)	0.1411** (0.416)	-0 1414* (0.415)	-0.1401* (0 418)	-0.2816*** (5 846)	-0.1411** (0.107)	-0 1413** (0.108)	-0.1410* (0.109)	-0.1419** (0.105)	-0.1414** (0.202)	-0.2825** (3.126)
Three-Factor CAPM	-0.3393** (0.303)	-0.3380** (0.312)	-0.3391** (0.307)	-0.3377** (0.309)	-0.3392** (0.312)	-0.6785** (4.682)	-0.2327** (0.343)	-0.2317** (0.341)	-0.2337** (0.344)	-0.2357** (0.346)	-0.3397** (0.448)	-0.5724*** (5.837)
Four-Factor Carhart	0.0531*** (0.139)	0.0531*** (0.119)	0.0532*** (0.132)	0.0538*** (0.138)	0.0533*** (0.134)	0.0002* (1.674)	0.0621*** (0 106)	0.0621*** (0.114)	0.0621*** (0.116)	0.0621*** (0.118)	0.0617*** (0.119)	-0.0004*** (3.946)

Four-Factor CAPM	-0.4354* (0.505)	-0.4350* (0.506)	-0.4352* (0.509)	-0.4351* (0.507)	-0.4359* (0 504)	-0.8713*** (6.972)	-0.4450*** (0.721)	-0.4454*** (0.724)	-0.4458*** (0.727)	-0.4457*** (0.729)	-0.3459*** (0.622)	-0.7909** (4.894)
Five-Factor CAPM	-0.6409* (0.124)	-0.6401* (0 114)	-0.6405* (0.144)	-0.6408* (0.194)	-0.6403* (0.134)	-1.2812** (4.892)	-0.8481*** (0.120)	-0.8470*** (0.122)	-0.8477*** (0.128)	-0.8488*** (0.125)	-0.7481*** (0.020)	-1.5962** (6.967)
India												
One-Factor CAPM	-0.5301*** (0.113)	-0.5062*** (0.123)	-0.5763*** (0.133)	-0.5967*** (0.143)	-0.618*** (0.213)	-1.149** (4.893)	-0.5216*** (0.369)	-0.5216*** (0.366)	-0.5216*** (0.362)	-0.5216*** (0.364)	-0.5168*** (0.467)	-1.038* (0.103)
Three-Factor CAPM	-0.7051*** (0.118)	-0.7052*** (0.128)	-0.7054*** (0.138)	-0.7057*** (0.178)	-0.7059*** (0.183)	-1.411** (4.783)	-0.5279*** (0.625)	-0.5289*** (0.656)	-0.5299*** (0 659)	-0.5219*** (0.658)	-0.6222*** (0.754)	-1.150* (0.118)
Four-Factor Carhart	0.2906*** (0.253)	0.2806*** (0.203)	0.2706*** (0.254)	0.2206*** (0.258)	0.2406*** (0.259)	-0.005** (3.957)	0.3606*** (0.700)	0.3608*** (0.701)	0.3609*** (0.708)	0.3603*** (0.707)	0.4607*** (0.806)	0.100* (0.453)
Four-Factor CAPM	-0.5002*** (0.158)	-0.5012*** (0.152)	-0.5013*** (0.153)	-0.5112*** (0.156)	-0.6017*** (0.251)	-1.101*** (5.963)	-0.7030*** (0.497)	-0.7031*** (0.487)	-0.7034*** (0.457)	-0.7033*** (0.497)	-0.8038*** (0.597)	-1 506** (0.558)
Five-Factor CAPM	-0 1052*** (0.177)	-0.1053*** (0.187)	-0 1059*** (0 172)	-0 1057*** (0.171)	-0.1054*** (0.176)	-0.210** (3.783)	-0.4100*** (0.502)	-0.4122*** (0.503)	-0.4133*** (0.504)	-0.4322*** (0.508)	-0.4124*** (0.507)	-0.8224** (0.377)
China												
One-Factor CAPM	-0.1219** (0.817)	-0.1229** (0.812)	-0.1269** (0.813)	-0 1279** (0.818)	-0.1269** (0.811)	-0.248** (3.957)	-0.0425*** (0.572)	-0.0424*** (0.572)	-0.0427*** (0 505)	-0.0420*** (0.572)	-0.1421*** (0.672)	-0.1846** (3.573)
Three-Factor CAPM	-0.0099*** (0.719)	-0.0089*** (0.729)	-0.0079*** (0.739)	-0.0083*** (0.733)	-0.0081*** (0.722)	-0.018** (4.936)	-0.0743*** (0.875)	-0.0741*** (0.870)	-0.0740*** (0.871)	-0.0744*** (0.877)	-0.0843*** (0.978)	-0.1586** (4.968)
Four-Factor Carhart	-0.1159* (0.102)	-0.1150** (0.122)	-0.1152* (0.132)	-0.1153* (0 131)	-0.1154** (0.134)	-0.2313** (4.384)	-0.2618* (0.1820)	-0.2619* (0.1822)	-0.2616* (0 1824)	-0.2612* (0.1827)	-0.3618* (0.2824)	-0 623** (5 783)
Four-Factor CAPM	-0.0207* (0.801)	-0.0208* (0.802)	-0.0202* (0.806)	-0.0209* (0.808)	-0.0203* (0.807)	-0.041** (3.839)	-0.0351*** (0.606)	-0.0352*** (0.607)	-0.0355*** (0.602)	-0.0356*** (0.603)	-0.1358*** (0.706)	-0.170** (4.975)
Five-Factor CAPM	-0.0742*** (0.781)	-0.0741*** (0.783)	-0.0744*** (0.786)	-0.0747*** (0 787)	-0.0748*** (0 781)	-0.149** (3.957)	-0.0819*** (0.114)	-0.0812*** (0.124)	-0.0813*** (0 116)	-0.0819*** (0.117)	-0.1819*** (0.212)	-0.263* (4.927)
South Africa												
One-Factor CAPM	0 0257*** (0.451)	0.0261*** (0.431)	0.0211*** (0.419)	0.0221*** (0.265)	0.0112*** (0.111)	-0.0145** (3.868)	0.1131*** (0.327)	0.1133*** (0.326)	0.1132*** (0.328)	0.1136*** (0.324)	0.0130*** (0.227)	-0.100** (5.453)
Three-Factor CAPM	-0.2233*** (0.312)	-0.2234*** (0.312)	-0.2235*** (0.316)	-0.2237*** (0.310)	-0.1233*** (0.309)	-0 3466** (5.673)	-0.2103*** (0.629)	-0.2102*** (0.623)	-0.2106*** (0.625)	-0.2107*** (0.622)	-0.2105*** (0.620)	-0.00002* (3.895)
Four-Factor Carhart	-0.1190*** (0.565)	-0.1192*** (0.561)	-0 1196*** (0.562)	-0.1198*** (0.564)	-0.2190*** (0.665)	-0.338** (4.392)	-0.0439*** (0.128)	-0.0435*** (0.121)	-0.0433*** (0.129)	-0.0432*** (0.132)	-0.1437*** (0.222)	-0.0998** (3.967)

Four-Factor CAPM	-0.0282*** (0.227)	-0.0288*** (0.217)	-0.0284*** (0.222)	-0.0283*** (0.225)	-0.0184*** (0.127)	-0.046** (5.562)	-0.0980*** (0.131)	-0.0981*** (0.132)	-0.0982*** (0.134)	-0.0986*** (0.138)	-0.0989*** (0.139)	-0.0009* (3.078)
Five-Factor CAPM	-0.0303*** (0.751)	-0.0301*** (0.752)	-0.0305*** (0.755)	-0.0306*** (0.757)	-0.0308*** (0.758)	-0.0611** (4.893)	-0.0201*** (0.345)	-0.0221*** (0.323)	-0.0232*** (0.339)	-0.0264** (0.395)	-0.0128*** (0.271)	-0.0073*** (5.906)

Note: The table presents the results of ITR puzzle based on quintile of ITR portfolio analysis. The full sample is divided into liquid and illiquid firms then these two groups are further divided into quintile portfolios of ITR for all manufacturing firms of BRICS and Pakistan. Alpha is estimated using one-factor to five-factors CAPM and Carhart models. The Alpha along with their standard errors below in parentheses are presented. ***, **, * shows the level of significance for 1%, 5%, and 10% respectively.

Table 4.15: Idiosyncratic Tail Risk Puzzle in Financially Constrained and Unconstrained Firms

	Financially Constrained Firms						Financially Unconstrained Firms					
Portfolios / Models	ITR1	ITR2	ITR3	ITR4	ITR5	ITR5-ITR1	ITR1	ITR2	ITR3	ITR4	ITR5	ITR5-ITR1
Pakistan												
One-Factor CAPM	0.5121* (0.002)	0.5118** (0.112)	0.5115* (0.013)	0.5112*** (0.007)	0.5109** (0.005)	-0.0012* (3.212)	0.6855*** (0.029)	0.6850** (0.006)	0.6844* (0.128)	0.6839** (0.005)	0.6830** (0.001)	-0.0025* (1.004)
Three-Factor CAPM	-0.3211*** (0.127)	-0.3210** (0.012)	-0.3207* (0.009)	-0.3204*** (0.021)	-0.3201* (0.008)	0.0010** (3.201)	-0.8895*** (0.04)	-0.8890* (0.007)	-0.8884** (0.009)	-0.8879* (0.281)	-0.8872*** (0.271)	0.0023** (1.056)
Four-Factor Carhart	-0.2890** (0.169)	-0.2885*** (0.280)	-0.2881* (0.211)	-0.2877*** (0.010)	-0.2871** (0.015)	0.0019* (3.217)	-0.6409** (0.160)	-0.6406* (0.220)	-0.6397*** (0.120)	-0.6389* (0.119)	-0.6384** (0.299)	0.0025** (1.082)
Four-Factor CAPM	-0.3405** (0.012)	-0.3400*** (0.011)	-0.3396* (0.212)	-0.3391** (0.010)	-0.3389** (0.111)	0.0016* (1.221)	-0.3545** (0.241)	-0.3588* (0.130)	-0.3582*** (0.217)	-0.3575* (0.019)	-0.3566* (0.013)	-0.0021** (1.782)
Five-Factor CAPM	-0.5890* (0.210)	-0.5880*** (0.200)	-0.5878** (0.201)	-0.5870* (0.171)	-0.5865** (0.113)	0.0025*** (2.221)	-0.9367* (0.160)	-0.9359** (0.134)	-0.9353* (0.119)	-0.9343** (0.111)	-0.9339** (0.100)	0.0028*** (1.102)
Brazil												
One-Factor CAPM	-0.1769* (0.011)	-0.1760** (0.121)	-0.1750*** (0.110)	-0.1740* (0.002)	-0.1730** (0.168)	0.0039*** (4.172)	-0.7759** (0.012)	-0.7750* (0.071)	-.7760** (0.052)	-0.7755*** (0.015)	-0.7740* (0.009)	0.0019** (7.217)
Three-Factor CAPM	-0.4198** (0.107)	-0.4190*** (0.015)	-0.4180** (0.010)	-0.4170* (0.017)	-0.4165** (0.111)	0.0033* (3.119)	-0.1941** (0.222)	-0.1930*** (0.071)	-0.1920* (0.008)	-0.1915** (0.029)	-0.1910*** (0.209)	0.0031*** (5.100)
Four-Factor Carhart	0.6219** (0.299)	0.6210*** (0.247)	0.6202** (0.201)	0.6197* (0.003)	0.6189** (0.001)	-0.0030*** (5.240)	0.2161* (0.124)	0.2150** (0.290)	0.2140* (0.014)	0.2130* (0.167)	0.2110*** (0.111)	-0.0051** (4.231)
Four-Factor CAPM	-0.4197*** (0.022)	-0.4189** (0.004)	-0.4180* (0.230)	-0.4175*** (0.105)	-0..4165* (0.018)	0.0032* (3.101)	-0.5715*** (0.041)	-0.5710** (0.170)	-0.5701* (0.109)	-0.5692** (0.266)	-0.5684*** (0.042)	0.0031** (5.033)

Five-Factor CAPM	-0.7280** (0.160)	-0.7270*** (0.198)	-0.7265* (0.070)	-0.7260*** (0.058)	-0.7255** (0.161)	0.0025* (4.210)	-0.9931* (0.210)	-0.9920** (0.094)	-0.9910** (0.092)	-0.9903** (0.069)	-0.9894*** (0.245)	0.0037** (3 017)
Russia												
One-Factor CAPM	0.1203* (0.055)	-0.1194** (0.087)	-0.1186* (0.015)	-0.1179* (0.006)	-0.1173*** (0 069)	-0.2376* (4.096)	-0.8939** (0.017)	-0.8929** (0.030)	-0.8918** (0.146)	-0.8906* (0.016)	-0 8889*** (0.066)	0.0050 (2.174)
Three-Factor CAPM	0 2348** (0.011)	-0.2340* (0.003)	-0.2330* (0.009)	-0 2320** (0.090)	-0.2310*** (0.091)	-0.4658** (3.076)	-0.6600* (0.033)	-0.6558* (0.202)	-0.6549** (0.087)	-0.6543*** (0.231)	-0.6535*** (0.129)	0.0065** (4.016)
Four-Factor Carhart	0.3212** (0.011)	0.3203* (0.009)	0.3191*** (0.007)	0.3181** (0 034)	0.3174* (0.002)	-0.0083*** (4.089)	0.3622** (0.234)	0.3612** (0.126)	0.3607** (0.090)	0.3599* (0.020)	0.3591*** (0.104)	-0.0031* (3.201)
Four-Factor CAPM	-0 5418*** (0.200)	-0.5411* (0.259)	-0.5402*** (0.026)	-0.5395* (0.030)	-0.5386*** (0.005)	-0.0059* 2.084)	-0.5545** (0.261)	-0.5530* (0.055)	-0.5510* (0.169)	-0.5490*** (0.103)	-0.5479* (0.027)	-0.0066*** (4.180)
Five-Factor CAPM	-0.7400** (0.038)	-0.7391*** (0.042)	-0.7386* (0.060)	-0.7377*** (0.102)	-0.7368** (0.040)	-0.0014** (6.273)	-0.7416* (0.202)	-0.7406*** (0.104)	-0.7398*** (0.066)	-0.7388*** (0.094)	-0.737*** (0.241)	-0.0039** (3.016)
India												
One-Factor CAPM	-0 9922* (0.156)	-0 9912** (0.007)	-0.9903*** (0.121)	-0.9893* (0.012)	-0.9882*** (0.251)	0.0040* (3.076)	-0.9943** (0.241)	-0.9935** (0.149)	-0.9927** (0.070)	-0.9916** (0.024)	-0.9905** (0.003)	0.0038* (3.009)
Three-Factor CAPM	-0.7832** (0.012)	-0.7822* (0.028)	-0.7810*** (0.046)	-0.7797** (0.011)	-0.7786* (0.059)	0.0046* (2.187)	-0.7540* (0.047)	-0.7520** (0.007)	-0.7508* (0.004)	-0.7501** (0.011)	-0.7492*** (0.016)	0.0048 (2.109)
Four-Factor Carhart	0.6890** (0.239)	0.6880* (0.263)	0.6871** (0 060)	0.6865* (0.279)	0.6855** (0.060)	-0.0035** (5.101)	0 6969* (0.151)	0.6957*** (0.002)	0.6950** (0.028)	0.6943** (0.085)	0.6934*** (0.078)	-0.0035** (7.032)
Four-Factor CAPM	-0.3890** (0.075)	-0.3880*** (0.040)	-0.3869** (0.057)	-0.3858* (0.050)	-0.3846** (0.048)	0.0044*** (3.030)	-0.3848** (0.239)	-0.3825** (0.117)	-0.3812* (0.095)	-0.3800* (0.086)	-0.3788** (0.045)	0.0060* (3.283)
Five-Factor CAPM	-0 5999** (0.041)	-0.5987* (0.043)	-0.5975** (0.050)	-0.5962** (0.211)	-0.5949** (0.006)	0.0050** (6 078)	-0.5569** (0.059)	-0.5559** (0.010)	-0.5547* (0 077)	-0.5538** (0.013)	-0.5530*' (0 036)	0.0039** (6.292)
China												
One-Factor CAPM	-0 7540** (0.207)	-0.7532* (0.200)	-0 7525** (0.277)	-0.7516*** (0.197)	-0.7504* (0.019)	0.0036* (3.468)	-0.7832** (0.002)	-0.7821* (0.023)	-0.7814** (0.013)	-0.7805* (0.079)	-0.7796** (0.151)	-0.0036* (4.272)
Three-Factor CAPM	-0.3890** (0.009)	0.3870*** (0.059)	0.3850* (0.041)	0 3839* (0.008)	0.3829** (0.026)	0.7719** (4.290)	-0.3340* (0.029)	-0.3331** (0.005)	-0.3322** (0.148)	-0.3310** (0.069)	-0.3298** (0.056)	0.0042** (4.004)
Four-Factor Carhart	-0.5930** (0.030)	-0.5918** (0.001)	-0.5906** (0.005)	-0.5898** (0.020)	-0.5878* (0.231)	0.0052** (3.187)	-0.6290** (0.018)	-0.6278** (0.239)	-0.6266** (0.140)	-0.6253** (0.249)	-0.6244* (0.151)	0.0046* (6.205)
Four-Factor CAPM	-0.6496** (0 233)	-0.6486** (0.133)	-0.6474* (0.166)	-0 6459** (0.087)	-0 6449** (0.239)	-0.0047** (4.123)	-0.6713*** (0.139)	-0.6701* (0.036)	-0.6693** (0.139)	-0.682* (0.041)	-0.6671*** (0.142)	0.0024** (7.679)
Five-Factor CAPM	-0.4330** (0.057)	-0.4320* (0 065)	-0.4308** (0.097)	-0.4296* (0.013)	-0.4284* (0.144)	0 0046** (3.287)	-0.4210* (0.247)	-0.4201** (0 025)	-0 4192* (0.247)	-0.4183*** (0.031)	-0.4172** (0.024)	0.0038** (3.073)

South Africa												
One-Factor CAPM	0.1589** (0.190)	0.1580* (0.047)	0.1570* (0.051)	0.1558** (0.103)	0.1550* (0.230)	-0.0030* (4.183)	0.1592*** (0.294)	0.1680** (0.012)	0.1563** (0.017)	0.1828* (0.035)	0.1708** (0.019)	-0.0084*** (5.173)
Three-Factor CAPM	0.3330* (0.105)	0.3300** (0.204)	0.3280** (0.080)	0.3268* (0.110)	0.3254** (0.201)	-0.0076* (3.172)	0.3138*** (0.030)	0.3117* (0.021)	0.3102* (0.039)	0.3077** (0.025)	0.3037* (0.040)	-0.0101** (7.083)
Four-Factor Carhart	-0.5934*** (0.209)	-0.5923* (0.118)	-0.5903** (0.112)	-0.5884** (0.128)	-0.5872*** (0.100)	0.0062** (6.172)	-0.7653*** (0.47)	-0.7640** (0.013)	-0.7622*** (0.018)	-0.7593* (0.029)	-0.7519*** (0.061)	-0.0134** (6.182)
Four-Factor CAPM	-0.7120** (0.107)	-0.7100** (0.245)	-0.7090*** (0.102)	-0.7074** (0.121)	-0.7061* (0.122)	-0.0059** (3.273)	-0.8137*** (0.300)	-0.8122* (0.015)	-0.8104** (0.019)	-0.8088** (0.020)	-0.8049** (0.174)	-0.0088*** (4.172)
Five-Factor CAPM	-0.9210* (0.269)	-0.9190* (0.150)	-0.9180** (0.101)	-0.9155*** (0.275)	-0.9135*** (0.138)	-0.0075 (5.178)	-0.8140*** (0.019)	-0.8122** (0.018)	-0.8102* (0.020)	-0.8084** (0.010)	-0.8057*** (0.123)	-0.0083*** (5.193)

Note: The table presents the results of the ITR puzzle. The full sample is divided into financially constrained and unconstrained firms then these two groups are further divided into quintile portfolios of ITR for all manufacturing firms of BRICS countries. Alpha is estimated using one factor to five factors CAPM models and presented along with their standard errors below in parentheses. ***, **, * shows the level of significance for 1%, 5%, and 10% respectively.

Table 4.16: Idiosyncratic Tail Risk Puzzle in High, Medium, and Low Beta Firms

Portfolios / Models	High Beta Firms						Medium Beta Firms						Low Beta Firms					
	ITR1	ITR2	ITR3	ITR4	ITR5	ITR5-ITR1	ITR1	ITR2	ITR3	ITR4	ITR5	ITR5-ITR1	ITR1	ITR2	ITR3	ITR4	ITR5	ITR5-ITR1
Pakistan																		
One-Factor CAPM	0.9800** (0.130)	0.9592* (0.008)	0.9576** (0.016)	0.9561* (0.015)	0.9600* (0.298)	0.0200** (5.200)	0.5776** (0.291)	0.5761* (0.076)	0.5749* (0.049)	0.5732*** (0.132)	0.5800** (0.180)	0.0024** (6.024)	0.3580** (0.102)	0.3568* (0.112)	0.3555** (0.155)	0.3537** (0.137)	0.3770** (0.170)	0.0190* (3.124)
Three-Factor CAPM	-0.7800* (0.006)	-0.7787** (0.013)	-0.7772* (0.015)	-0.7759** (0.013)	-0.7990** (0.219)	- 0.0190*** (4.190)	-0.4788* (0.028)	- 0.4771*** (0.077)	-0.4755** (0.055)	-0.4737** (0.037)	-0.4980** (0.098)	-0.0192* (4.192)	-0.5640* (0.131)	-0.5628** (0.128)	- 0.5616*** (0.016)	- 0.5598*** (0.198)	-0.5780** (0.178)	- 0.0140*** (3.140)
Four-actor Carhart	-0.6420* (0.230)	-0.6409** (0.011)	-0.6392** (0.017)	-0.6379** (0.213)	-0.6550* (0.055)	-0.0130** (5.130)	-0.1550** (0.160)	-0.1533** (0.033)	-0.1515* (0.115)	-0.1495** (0.195)	-0.1680* (0.168)	-0.0130** (6.130)	-0.7793** (0.107)	-0.7775* (0.176)	-0.7759** (0.077)	-0.7742** (0.142)	-0.7895** (0.089)	-0.0102** (4.102)
Four-Factor CAPM	- 0..3754** (0.260)	- 0.3740*** (0.014)	-0.3717* (0.023)	-0.3701** (0.216)	-0.3880** (0.88)	-0.0126* (4.126)	- 0.6430*** (0.130)	-0.6410** (0.010)	-0.6349** (0.139)	-0.6329** (0.219)	-0.6600** (0.066)	-0.0170* (5.019)	-- 0.8276** (0.243)	-0.8264* (0.240)	-0.8246** (0.046)	-0.8228** (0.228)	-0.8446* (0.146)	- 0.0170*** (4.170)
Five-Factor CAPM	-0.2200** (0.063)	-02187* (0.013)	-0.2168** (0.019)	- 0.2145*** (0.123)	-0.2400** (0.244)	-0.0200* (5.200)	-0.9550* (0.050)	-0.9532** (0.132)	-0.9513** (0.113)	-0.9495* (0.095)	-0.9980* (0.080)	-0.0430** (5.130)	- 0.1431*** (0.126)	-0.1417* (0.117)	-0.1399* (0.113)	-0.1377** (0.137)	-0.1660** (0.166)	-0.0229** (4.229)
Brazil																		
One-Factor CAPM	-0.2760** (0.192)	-0.2741** (0.041)	-0.2726** (0.144)	-0.2706** (0.201)	-0.2891** (0.191)	-0.0131** (3.131)	-0.9690** (0.190)	-0.9665** (0.042)	-0.9640* (0.040)	-0.9617** (0.017)	-0.9789** (0.189)	- 0.0099*** (3.099)	- 0.1342*** (0.054)	-0.1330** (0.131)	-0.1300* (0.013)	-0.1265** (0.207)	-0.1552** (0.041)	-0.0210** (5.29)
Three-Factor CAPM	-0.5906* (0.108)	- 0.5888*** (0.088)	-0.5868** (0.069)	-0.5843** (0.139)	- 0.5992*** (0.197)	- 0.0086*** (3.008)	-0.7223** (0.113)	-0.7198** (0.148)	-0.7171** (0.171)	-0.7146** (0.246)	-0.7345* (0.046)	-0.0122** (4.024)	-0.8951** (0.025)	-0.8936** (0.006)	-0.8900 ** (0.009)	-0.8868** (0.070)	-0.8998** (0.191)	- 0.0047*** (4.004)
Four-actor Carhart	0.9340** (0.140)	0.9320** (0.120)	0.9302** (0.196)	0.9274*** (0.174)	0.9560** (0.160)	0.0220** (3.220)	0.3546** (0.115)	0.3521*** (0.121)	0.3490* (0.016)	0.3466** (0.166)	0.3760*** (0.067)	0.0124* (3.012)	0.7570*** (0.087)	0.7541* (0.056)	0.7516* (0.061)	0.7479*** (0.095)	0.7876*** (0.154)	0.0306** (3.186)
Four-Factor CAPM	- 0.3720*** (0.107)	- 0.3704*** (0.106)	-0.3689** (0.155)	-0.3664** (0.164)	-0.3892** (0.098)	-0.0172** (3.071)	- 0.4810*** (0.177)	-0.4722** (0.122)	-0.4696** (0.196)	- 0.4677*** (0.277)	-0.4996** (0.197)	- 0.0186*** (3.089)	- 0.5471*** (0.034)	- 0.5436*** (0.236)	- 0.5406*** (0.206)	-0.5374** (0.172)	-0.5676* (0.179)	-0.0205* (3.131)
Five-Factor CAPM	-0.7500* (0.256)	-0.7470** (0.006)	-0.7450* (0.021)	- 0.7424*** (0.124)	-0.7681** (0.061)	- 0.0181*** (4.181)	- 0.1910*** (0.189)	- 0.1884*** (0.086)	-0.1857* (0.157)	- 0.1828*** (0.130)	-0.1999* (0.299)	-0.0089** (3.180)	- 0.9324*** (0.126)	- 0.9290*** (0.127)	-0.9250** (0.101)	-0.9205* (0.109)	-0.9568** (0.199)	-0.0244** (3.241)
Russia																		
One-Factor CAPM	-0.7244** (0.044)	- 0.7230*** (0.230)	-0.7191** (0.019)	0.7158** (0.058)	-0.7540** (0.040)	-0.0296** (3.096)	- 0.9420*** (0.105)	-0.9385** (0.038)	-0.9358** (0.058)	0.9321** (0.021)	-0.9660** (0.060)	-0.0240** (4.022)	-0.1320* (0.120)	-0.1304** (0.104)	-0.1275** (0.127)	-0.1235** (0.124)	-0.1425* (0.014)	-0.0105** (6.121)

Three-Factor CAPM	-0.5940* (0.140)	- 0.5930** (0.130)	-0.5895* (0.095)	-0.5866** (0.166)	- 0.5998*** (0.099)	- 0.0058*** (2.085)	-0.7453** (0.035)	-0.7427* (0.027)	-0.7399** (0.099)	- 0.7371*** (0.071)	-0.7560* (0.075)	- 0.0107*** (5.107)	-0.3465** (0.064)	- 0.3443*** (0.144)	-0.3428* (0.128)	-0.3401** (0.101)	-0.3560** (0.160)	-0.0095* (4.070)
Four-factor Carhart	0.6320* (0.120)	0.6294** (0.194)	0.6262** (0.226)	0.6233** (0.103)	0.6440* (0.044)	0.0120** (3.120)	0.5342** (0.142)	0.5313** (0.113)	0.5283** (0.149)	0.5246** (0.046)	0.5440** (0.144)	0.0098** (3.029)	0.7511** (0.011)	0.7484* (0.184)	0.7467** (0.177)	0.7447* (0.147)	0.7645* (0.201)	0.0134* (5.103)
Four-Factor CAPM	-0.4901* (0.101)	-0.4866** (0.0066)	-0.4832** (0.032)	-0.4806** (0.106)	-0.4997** (0.099)	-0.0096* (5.006)	- 0.1859*** (0.018)	-0.1827* (0.027)	-0.1798* (0.178)	-0.1771** (0.171)	-0.1991** (0.187)	-0.0132* (4.132)	- 0.5331*** (0.035)	-0.5308** (0.108)	- 0.5283*** (0.123)	- 0.5260** (0.026)	-0.5549* (0.147)	-0.0218** (3.121)
Five-Factor CAPM	-0.9921** (0.1211)	- 0.9883*** (0.083)	-0.9848** (0.034)	-0.9811** (0.032)	- 0.9980*** (0.180)	-0.0059 (4.059)	-0.3430* (0.130)	- 0.3393*** (0.019)	- 0.3374*** (0.020)	-0.3355** (0.055)	-0.3541** (0.141)	- 0.0111*** (3.111)	-0.2734* (0.134)	-0.2715** (0.017)	-0.2696* (0.144)	-0.2681* (0.181)	-0.2893** (0.145)	-0.0159* (4.141)
India																		
One-Factor CAPM	-0.1363** (0.103)	-0.1301* (0.100)	-0.1278** (0.005)	-0.1254* (0.204)	-0.1444** (0.145)	-0.0081** (4.107)	-0.8604** (0.204)	-0.8578** (0.230)	- 0.8549*** (0.049)	-0.8523** (0.023)	-0.8705* (0.128)	- 0.0101*** (4.001)	-0.9325** (0.196)	-0.9296* (0.196)	-0.9263** (0.011)	-0.9225** (0.120)	-0.9460* (0.092)	-0.0135** (8.081)
Three-Factor CAPM	-0.3210* (0.171)	-0.3175** (0.003)	-0.3152* (0.255)	-0.3119** (0.004)	- 0.3300*** (0.002)	- 0.0090*** (3.190)	-0.6431* (0.031)	-0.6398* (0.217)	-0.6373** (0.204)	-0.6340** (0.004)	-0.6780** (0.089)	-0.0349** (6.039)	-0.7664** (0.166)	-0.7645** (0.204)	-0.7618** (0.118)	-0.7589* (0.090)	-0.7883** (0.083)	-0.0219* (6.220)
Four-factor Carhart	0.5532** (0.109)	0.5506** (0.133)	0.5489*** (0.189)	0.5472* (0.069)	0.5686** (0.056)	0.0154** (4.121)	0.4550*** (0.050)	0.4514** (0.051)	0.4487*** (0.087)	0.4450* (0.019)	0.4761* (0.161)	0.0211** (5.90)	0.1801*** (0.181)	0.1772** (0.223)	0.1754* (0.117)	0.1721** (0.021)	0.1906*** (0.068)	0.0105** (4.180)
Four-Factor CAPM	-0.7232* (0.101)	-0.7199* (0.009)	-0.7172** (0.125)	-0.7153** (0.101)	- 0.7546*** (0.146)	-0.0314** (5.214)	-0.3231** (0.103)	-0.3196** (0.161)	-0.3161** (0.110)	- 0.3122*** (0.012)	-0.3421** (0.009)	-0.0190** (4.048)	-0.5671** (0.267)	-0.5652** (0.153)	-0.5635** (0.105)	-0.5598** (0.055)	-0.5789** (0.078)	- 0.0118*** (6.116)
Five-Factor CAPM	- 0.1980*** (0.217)	- 0.1953*** (0.201)	- 0.1926*** (0.121)	-0.1903** (0.154)	-0.1997** (0.012)	-0.0170** (5.234)	-0.7333** (0.273)	-0.7309** (0.208)	-0.7294** (0.194)	-0.7265* (0.165)	-0.7532* (0.020)	-0.0199* (7.099)	- 0.3761*** (0.213)	-0.3733** (0.039)	-0.3700* (0.007)	-0.3639* (0.014)	-0.3883** (0.083)	-0.0122 (5.227)
China																		
One-Factor CAPM	-0.1874* (0.131)	-0.1842** (0.043)	- 0.1821*** (0.028)	-0.1808* (0.004)	-0.1899** (0.018)	-0.0025* (4.027)	-0.4241** (0.130)	-0.4215* (0.107)	-0.4205** (0.007)	-0.4189* (0.190)	-0.4320** (0.243)	-0.0079** (6.056)	-0.5672** (0.203)	-0.5655** (0.206)	- 0.5630*** (0.281)	-0.5597** (0.199)	- 0.5783*** (0.184)	-0.0111** (3.006)
Three-Factor CAPM	-0.3448** (0.133)	-0.3429* (0.131)	-0.3413** (0.013)	-0.3401* (0.049)	-0.3681* (0.082)	- 0.0233*** (5.233)	-0.9237* (0.139)	- 0.9212*** (0.218)	-0.9174* (0.277)	-0.9148** (0.209)	-0.9443* (0.266)	- 0.0206*** (5.208)	-0.8321** (0.222)	- 0.8210*** (0.214)	-0.8155** (0.209)	-0.8100* (0.101)	-0.8525** (0.226)	-0.0204* (4.108)
Four-factor Carhart	-0.5472** (0.054)	- 0.5449*** (0.149)	-0.5422* (0.124)	-0.5401** (0.101)	-0.5661* (0.061)	-0.0189** (4.180)	- 0.7232*** (0.255)	-0.7193** (0.256)	-0.7166** (0.154)	-0.7143** (0.251)	- 0.7561*** (0.250)	-0.0329** (5.120)	- 0.2730*** (0.157)	-0.2680** (0.182)	-0.2651* (0.251)	-0.2621** (0.029)	-0.2891* (0.190)	-0.0161** (3.001)
Four-Factor CAPM	-0.7432* (0.231)	-0.7399* (0.094)	-0.7378** (0.074)	-0.7355* (0.056)	-0.7789** (0.089)	-0.0357* (4.067)	-0.3130** (0.138)	-0.3117* (0.172)	-0.3098** (0.144)	-0.3079** (0.244)	-0.3342* (0.028)	-0.212* (4.012)	-0.7612** (0.137)	-0.7583* (0.219)	- 0.7550*** (0.050)	-0.7521** (0.235)	-0.7812** (0.213)	-0.0200* (4.023)

Five-Factor CAPM	-0.2761*** (0.061)	-0.2748** (0.049)	-0.2725* (0.026)	-0.2706** (0.008)	-0.2890** (0.133)	-0.0129** (3.030)	-0.4710** (0.041)	-0.4685** (0.231)	-0.4649** (0.127)	-0.4619** (0.219)	-0.4804* (0.143)	-0.0094** (4.002)	-0.1286** (0.076)	-0.1236** (0.149)	-0.1249* (0.159)	-0.1204* (0.015)	-0.1562* (0.041)	-0.0276** (6.012)
South Africa																		
One-Factor CAPM	0.2359** (0.012)	0.2326* (0.212)	0.2301** (0.211)	0.2265* (0.066)	0.2469*** (0.022)	0.0110** (4.311)	0.8712** (0.121)	0.8679** (0.132)	0.8642*** (0.221)	0.8611** (0.224)	0.8891*** (0.213)	0.0179* (4.367)	0.1421** (0.221)	0.1388* (0.002)	0.1352** (0.121)	0.1315* (0.094)	0.1560** (0.229)	0.0139* (5.387)
Three-Factor CAPM	-0.5417*** (0.121)	-0.5380*** (0.009)	-0.5348** (0.002)	-0.5313* (0.017)	-0.5561** (0.119)	-1.0978* (4.441)	-0.4523* (0.112)	-0.4486** (0.211)	-0.4449** (0.112)	-0.4415* (0.114)	0.4678* (0.029)	-0.7555** (3.066)	-0.7220*** (0.220)	-0.7184** (0.012)	-0.7154*** (0.009)	-0.7121** (0.123)	-0.7564** (0.009)	0.0344** (4.109)
Four-actor Carhart	-0.9437* (0.021)	-0.9399** (0.214)	-0.9361* (0.215)	-0.9333* (0.034)	-0.9672** (0.217)	-1.9109* (3.632)	-0.6783*** (0.215)	-0.6754** (0.115)	-0.6718* (0.145)	-0.6680** (0.019)	-0.6990** (0.127)	-0.8207* (4.105)	-0.8190** (0.001)	-0.8153 (0.011)	-0.8116 (0.115)	-0.8078* (0.005)	-0.8245** (0.006)	-0.0055* (4.101)
Four-Factor CAPM	-0.7210** (0.018)	-0.7171* (0.288)	-0.7137** (0.182)	-0.7111 * (0.124)	-0.7421** (0.284)	-0.1211*** (5.712)	-0.1325* (0.126)	-0.1289*** (0.214)	-0.1259** (0.218)	-0.1226*** (0.130)	0.1427** (0.127)	-0.5102** (5.131)	-0.5620* (0.026)	-0.5587** (0.024)	-0.5551** (0.138)	-0.5515*** (0.125)	0.5761** (0.137)	0.0096* (4.296)
Five-Factor CAPM	-0.3421*** (0.025)	-0.3388*** (0.215)	-0.3345* (0.244)	-0.3310* (0.016)	-0.3557** (0.213)	-0.0136* (4.275)	-0.9211*** (0.116)	-0.9175* (0.211)	-0.9136** (0.109)	-0.9103* (0.161)	0.9430*** (0.103)	-0.0219 (4.007)	-0.9220** (0.126)	-0.9183* (0.037)	-0.9151* (0.124)	-0.9124** (0.126)	-0.9350* (0.133)	0.0130** (3.067)

Note: The table presents the results of the ITR puzzle. The full sample is divided into high, medium, and low beta firms. Then, these three groups are further divided into quintile portfolios of IR for all manufacturing firms of BRICS countries. Alpha is estimated using one factor to five factors CAPM models and presented along with their standard errors below in parentheses. ***, **, * shows the level of significance for 1%, 5%, and 10% respectively.

In sum, the results for Russia, China, and South Africa also show the existence of the ITR puzzle for all three groups and in all CAPM models . However, we cannot distinguish which group of firms are more exposed due to ITR. Based on the findings, it can be argued that all asset pricing models produce more or less identical outcomes; only the magnitude of alpha values changes across different estimated models. Moreover, investors interested in ITR premiums might consider the Carhart models for Brazil, Russia, and India for better investment returns. Further, investors can be able to get potentially abnormal returns based on considering the Carhart model than the Fama-French asset pricing models

4.10. Jump Risk Puzzle

Our seventh and eighth objectives are to examine the JR puzzle overall and in different groups of firms of all sample countries. Although there is overwhelming empirical evidence for jumps in stock prices, very few studies examined the relationship between JR and stock returns. To our best knowledge, none of the studies examined the relationship between positive and negative jumps with their stock returns. For this, we run quantile regression, and the results are presented in Table 4.17 Part A. Based on the quantile regression results, we found interesting results favouring the JR puzzle. JR's coefficient values decrease from 20% to 80% quantile and have a significant negative relationship with their stock returns at any acceptable significance level. These findings support our hypothesis that high negative jumps earn lower returns than their counterpart.

Interestingly, these results are similar for all sample countries. However, a 20% quantile, positive and insignificant relationship is found between JR and stock returns. The coefficients for JR remain highly significant after controlling for all conventional risk factors, and JR plays a significant role in the expected returns.

The relationship between upper JR and stock returns results is shown in Table 4.17 Part B. For the 20% quantile, a significant negative relationship exists between upper JR and stock returns for all sample countries except China. After that, the coefficient values of JR from 40% to 80% there is a significant positive relationship. The findings of OLS also show the significant positive values coefficient of JR is found for every country.

In sum, the findings of upper JR show that stocks with upper jumps have positive returns, and in contrast, those firms with jumps on the negative side also have negative returns. This dilemma is called the JR puzzle, which contradicts the results of standard finance theory, which states that risky stocks should have high returns too.

Table 4.17: Jump Risk Puzzle through Quintile Regression via Negative Jumps

Part A Negative Jump Distribution

		Brazil			
		Quantiles			**OLS**
Variables	**20%**	**40%**	**60%**	**80%**	
Constant					0.0298**
					(0.778)
Jump Risk	0.1088	-0.7164*	-1.8029*	-1.7135**	-0.4153***
	(0.668)	(0. 443)	(1.324)	(1.834)	(0.047)
Return Reversal	0.0606**	0.2591*	0.4512*	0.4560**	0.330**
	(0.730)	(0.324)	(0.625)	(0.902)	(0.204)
Momentum Returns	-0.9132*	0.3027*	0.3816**	-0.1570*	0.8284*
	(0.186)	(0.422)	(0.734)	(0.251)	(0.206)
Market to Book Ratio	0.3480*	0.5466*	0.8775**	0.3897*	0.1137***
	(0.518)	(0.528)	(1.274)	(0.4681)	(1.898)
Downside Co-skewness	-0.0928**	-0.1648*	-0.7947	-0.5761**	-0.1030***
	(0.255)	(0.915)	(0.242)	(0.135)	(0.246)
Systematic Risk	-0.5090*	-0.4451*	.-0.1395*	-0.4350**	-0.0141**
	(0.914)	(0.171)	(0.287)	(0.1423)	(0.142)
		Russia			
Constant					0.2652*
					(0.897)
Jump Risk	-0.3882*	-0.3680*	-0.7394 **	-1.3501**	-1.5512***
	(0.680)	(0.816)	(0.471)	(0.120)	(0.2936)
Return Reversal	0.8348*	0.9047	1.7931	1.5162**	1.6093***
	(0.939)	(0.1381)	(0.169)	(0.264)	(0.182)

Momentum Returns	0.0885*	0.9075*	0.9074**	0.8999***	0.8457***
	(0.237)	(0.108)	(0.124)	(0.239)	(0.104)
Market to Book Ratio	0.2151*	0.2694**	1.9615*	1.9489**	1.8791***
	(0.447)	(1.334)	(1.385)	(1.210)	(1.241)
Downside Co-skewness	-0.1886*	-0.3000**	-0.3761**	-0.1066*	-0.1461**
	(0.472)	(0.631)	(0.672)	(0.237)	(0.1210)
Systematic Risk	-0.5537*	-0.8808**	0.7348*	0.3706*	0.6676**
	(0.212)	(0.237)	(0.217)	(0.2647)	(0.706)
			India		
Constant					0.6686*
					(0.979)
Jump Risk	-0.9761*	-0.9529**	- 0.8305**	-0.9786**	-0.5468**
	(0.452)	(0.464)	(0.481)	(0.467)	(0.518)
Return Reversal	0.2503*	0.4133*	0.9515*	0.7485*	0.6327***
	(0.961)	(0.969)	(0.835)	(0.538)	(0.215)
Momentum Returns	0.3543	0.5905***	0.9064**	0.6567**	0.6697**
	(0.895)	(0.915)	(0.124)	(0.418)	(0.221)
Market to Book Ratio	0.3778*	0.1593**	0.1791**	0.1781***	0.1770***
	(0.128)	(1.945)	(0.104)	(0.154)	(1.713)
Downside Co-skewness	-0.8334***	-0.6897**	-0.5460*	-0.6228**	-0.6225**
	(1.363)	(1.637)	(1.067)	(1.597)	(1.373)
Systematic Risk	-0.1614**	-0.16808*	-0.1696**	-0.1261*	-0.3252***
	(0.435)	(0.352)	(0.309)	(0.204)	(0.664)
			China		
Constant					0.1380**
					(0.038)
Jump Risk	0.0388	-0.0364*	-0.0529*	-0.0713**	-0.4153***
	(0.016)	(0. 044)	(0.324)	(0.314)	(0.347)
Return Reversal	-0.1760	-0.1450*	-0.1412*	-0.1450*	-0.1330**
	(0.027)	(0.022)	(0.022)	(0.032)	(0.023)
Momentum Returns	0.1328*	0.1302	0.1381*	0.1572*	0.1274***
	(0.163)	(0.673)	(0.792)	(0.825	(0.901)
Market to Book Ratio	0.4199**	0.4623*	0.4187*	0.0487**	0.4527***
	(0.151)	(0.568)	(0.472)	(0.468)	(0.451)
Downside Co-skewness	-0.0288*	-0.0164*	-0.0794*	-0.0576**	-0.0103***
	(0.025)	(0.015)	(0.042)	(0.035)	(0.025)
Systematic Risk	-0.0590	-0.0445*	-0.0439**	-0.0435*	-0.0414**
	(0.014)	(0.017)	(0.028)	(0.014)	(0.014)
			South Africa		
Constant					0.2652**
					(0.897)
Jump Risk	-0.3882	-0.3680*	-0.3782***	-0.3501**	-0.3155**
	(0.680)	(0.621)	(0.471)	(0.412)	(2.936)
Return Reversal	0.0834*	0.0804**	0.0179**	0.0162**	0.01636***
	(0.939)	(0.1381)	(0.1695)	(0.264)	(0.182)
Momentum Returns	0.8852*	0.9076**	0.9074***	0.8999**	0.8457***
	(0.237)	(0.108)	(0.124)	(0.239)	(0.010)
Market to Book Ratio	0.2114**	0.2694*	0.1965**	0.1894*	0.1879*
	(0.472)	(0.433)	(0.385)	(0.434)	(0.453)
Downside Co-skewness	-0.3188**	-0.3006*	-0.376**	-0.3109**	-0.3014***
	(0.472)	(0.631)	(0.672)	(0.623)	(0.6121)
Systematic Risk	-0.0553*	-0.0880**	-0.0534**	-0.0576 ***	-0.0606**
	(0.126)	(0.123)	(0.217)	(0.264)	(0.206)

Quintile Regression via Positive Jumps

Part B Positive Jump Distribution

Variables	20%	40%	60%	80%	OLS
Brazil					
Constant					0.0828*
					(0.378)
Jump Risk	-0.0112	-0.1467	1.2289**	1.3157***	0.4345**
	(0.168)	(0. 344)	(1.434)	(1.548)	(0.732)
Return Reversal	0.0660*	0.1259**	0.2245***	0.3456*	0.633***
	(0.370)	(0.534)	(0.756)	(0.829)	(0.924)
Momentum Returns	-0.1239**	0.2307	0.3368***	0.5243**	0.8288**
	(0.168)	(0.244)	(0.347)	(0.725)	(0.826)
Market to Book Ratio	0.3408**	0.4645***	0.5778*	0.8789**	0.9117*
	(0.215)	(0.358)	(1.427)	(1.5468)	(1.988)
Downside Co-skewness	-0.0289*	-0.2168	-0.4779	-0.5567***	-0.9233*
	(0.251)	(0.259)	(0.324)	(0.675)	(0.943)
Systematic Risk	-0.0905**	-0.1455	.-0.1539***	-0.8035*	-0.9114***
	(0.491)	(0.729)	(0.827)	(0.9234)	(0.914)
Russia					
Constant					0.2526**
					(0.978)
Jump Risk	-0.2388***	0.3638**	0.4479 *	1.6035***	1.7552*
	(0.086)	(0.168)	(0.187)	(0.201)	(0.3692)
Return Reversal	0.2438**	0.3479	1.1379	1.3256*	1.4069*
	(0.399)	(0.4831)	(0.696)	(0.862)	(0.921)
Momentum Returns	0.0588**	0.0699***	0.1409*	0.1899*	0.2478*
	(0.372)	(0.481)	(0.514)	(0.792)	(0.801)
Market to Book Ratio	0.1251**	0.2469***	1.5169***	1.8948*	1.9187**
	(0.247)	(1.343)	(1.538)	(1.610)	(1.740)
Downside Co-skewness	-0.1688**	-0.3340***	0.3716*	0.6066**	0.8461***
	(0.427)	(0.613)	(0.762)	(0.781)	(0.9211)
Systematic Risk	-0.5537**	-0.6631*	0.7348*	0.3706*	0.6676**
	(0.221)		(0.271)	(0.3456)	(0.806)
India					
Constant					0.7666**
					(0.997)
Jump Risk	-0.9121**	0.9529*	0.9605***	0.9768***	0.9968*
	(0.425)	(0.542)	(0.582)	(0.584)	(0.591)
Return Reversal	0.2530**	0.4142***	0.5142**	0.7458**	0.8327*
	(0.912)	(0.935)	(0.943)	(0.958)	(0.976)
Momentum Returns	0.2543	0.5405**	0.7034*	0.9567***	0.9697*
	(0.859)	(0.975)	(0.994)	(0.996)	(0.998)
Market to Book Ratio	0.1778**	0.2593***	0.4791*	0.5781**	0.8770*
	(0.228)	(0.445)	(0.704)	(0.954)	(1.413)
Downside Co-skewness	-0.3334*	-0.5897***	-0.5960**	-0.6228*	-0.6329**
	(1.463)	(1.637)	(1.867)	(1.927)	(1.973)
Systematic Risk	-0.2614*	-0.36808*	-0.4696***	-0.7261**	-0.9252**
	(0.135)	(0.322)	(0.379)	(0.404)	(0.664)
China					
Constant					0.1880*
					(0.058)
Jump Risk	0.1288	-0.2364**	0.3529**	0.3713**	0.4153**
	(0.116)	(0. 144)	(0.324)	(0.354)	(0.397)

Return Reversal	-0.1760	0.1850**	0.1912***	0.1950**	0.9930*
	(0.127)	(0.222)	(0.312)	(0.532)	(0.723)
Momentum Returns	0.1428**	0.1502	0.1681***	0.1972***	0.1977*
	(0.163)	(0.273)	(0.412)	(0.525	(0.921)
Market to Book Ratio	0.2199*	0.2613*	0.4817**	0.7487*	0.9527**
	(0.211)	(0.268)	(0.372)	(0.458)	(0.471)
Downside Co-skewness	-0.1288**	-0.2164**	-0.3794**	-0.4576*	-0.5103*
	(0.125)	(0.215)	(0.342)	(0.535)	(0.725)
Systematic Risk	-0.1590	-0.2445*	-0.3439**	-0.4435*	-0.6414*
	(0.114)	(0.207)	(0.328)	(0.614)	(0.914)
		South Africa			
Constant					0.2352*
					(0.877)
Jump Risk	-0.1882	0.2680*	0.4782***	0.5501**	0.6255**
	(0.670)	(0.691)	(0.771)	(0.812)	(2.336)
Return Reversal	0.1834**	0.2804*	0.3179***	0.4162**	0.71636*
	(0.939)	(0.9481)	(0.9695)	(0.994)	(0.999)
Momentum Returns	0.5852**	0.8076*	0.9074*	0.9912***	0.9957*
	(0.133)	(0.178)	(0.184)	(0.439)	(0.710)
Market to Book Ratio	0.2114*	0.2694**	0.1965*	0.1894**	0.1879**
	(0.427)	(0.631)	(0.785)	(0.834)	(0.953)
Downside Co-skewness	-0.3188**	-0.3226*	-0.366*	-0.3709***	-0.3814*
	(0.372)	(0.431)	(0.632)	(0.823)	(0.9121)
Systematic Risk	-0.1553**	-0.2880**	-0.3 534***	-0.3576 ***	-0.4606***
	(0.126)	(0.143)	(0.217)	(0.274)	(0.256)

The higher jump intensity in stocks may result from higher sensitivity and awareness of investors. Jumps in asset prices are ubiquitous, yet the high price of jump risk observed empirically is commonly viewed as puzzling. The next objective is to examine the JR puzzle in different groups of firms. Table 4.18 shows the results of the JR puzzle for liquid and illiquid groups of firms. The table format follows the same pattern as for the IR and ITR puzzle for liquid and illiquid firms. In this table, we sort the liquid and illiquid firms based on the five quintiles of JR and apply the CAPM models from one-factor to five factors and the Carhart model. The table lists the alpha values (abnormal return performance) and their standard errors in parentheses. In the IR5-IR1 column, we list the *t* statistics to show the difference in alpha values between the groups of firms. This column determines whether a significant difference exists in alpha values and GRS *t* statistics among the extreme portfolios.

According to Boudt and Petitjean (2014) liquidity shocks are an important source of jump occurrences; any shock in liquidity interrupts the market equilibrium and causes jumps. Although, there is a clear indication of the JR puzzle for both groups. However, We find interesting results for illiquid for all sample countries. Specifically, we can observe that the alpha values of JR5 portfolios are negative and statistically Table 4.19 shows the results of the JR puzzle for FC and FUC groups of firms. We can observe that, in mostly models the FC group of firms have high exposure to JR. More or less for all countries, the alpha values of the highest portfolios JR5 clearly show substantially negative values, which show high exposure compared to FC, JR1 and FUC JR5 values of alpha. This different effect in these two groups reiterates the benefit of diversification in mitigating the JR.

When we compare the country vice JR exposure on stock returns, we can clearly observe that the values of difference column JR5-JR1 for FC firms statically high for Pakistan, Brazil, and Russia. On the other hand, there is also evidence of the JR puzzle for India, China and South Africa but we are unable to distinguish the intensity of JR exposure based on groups. Said differently, there is no systematic pattern exist of JR exposure in FC and FUC firms in some CAPM models the intensity of JR is more in FC firms as compared to their counterpart firms.

Table 4.20 shows the JR puzzle in low-, medium-, and high-beta-based firms. For Pakistan, high-beta firms show more exposure due to JR as alpha values for JR5. The difference column JR5-JR1 shows negative and statistically significant performance compared to their counterparts. When we observe the alpha values of JR5 for the emerging countries, we cannot clearly state that any specific group of firms have high exposure due to JR.

Table 4.18: Idiosyncratic Jump Risk Puzzle in Liquid and Illiquid Firms

Portfolio / Models	Liquid Firms						Illiquid Firms					
	JR1	JR2	JR3	JR4	JR5	JR5-JR1	JR1	JR2	JR3	JR4	JR5	JR5-JR1
Pakistan												
One-Factor CAPM	0.2871** (0.055)	0.2770* (0.056)	0 2735** (0.057)	0 2598** (0.058)	0.2565* (0.059)	-0.0306** (3.360)	0.2320** (0.121)	0.2291* (0.123)	0.2266*** (0.125)	0.2233* (0.127)	0.2201** (0.130)	-0.0119* (0.132)
Three-Factor CAPM	-0 3429** (0 030)	-0 3404* (0.032)	-0.3385*** (0.035)	-0 3362* (0.037)	-0.3332** (0.038)	-0.6761*** (3.490)	-0.3840** (0.122)	-0.3807* (0.124)	-0.3774** (0.126)	-0.3741* (0.128)	-0.3715** (0 130)	-0.7581** (7.957)
Four-Factor Carhart	-0.5618* (0.102)	-0.5590** (0.105)	-0 5561* (0.107)	-0.5538*** (0.109)	-0.5505* (0.111)	-1.112*** (3.673)	-0.5766* (0.201)	-0.5736*** (0.203)	-0.5714* (0.205)	-0.5689*** (0.207)	-0.5667** (0.210)	-1.1433* (3.927)
Four-Factor CAPM	-0.1308* (0.051)	-0.1286** (0.053)	-0 1261*** (0.056)	-0.1236* (0.057)	-0.1209** (0.059)	-0.2517* (3.894)	-0.1580* (0.030)	-0 1555** (0.033)	-0 1528*** (0.035)	-0.1495** (0.037)	-0.1472* (0.039)	-0.3052* (3.924)
Five-Factor CAPM	-0 6870** (0.251)	-0 6837* (0.252)	-0.6808*** (0.255)	-0.6782* (0.257)	-0.6751** (0.259)	-0.7438* (3.9475)	-0.6330** (0.063)	-0.6307* (0.064)	-0.6283*** (0.065)	-0.6257* (0.067)	-0.6230** (0.067)	-1.256** (3.028)
Brazil												
One-Factor CAPM	-0.7241* (0.109)	-0.7208** (0.111)	-0.7184*** (0.113)	-0.7161*** (0.115)	-0.7134** (0.117)	-1.4377* (2.673)	-0.7350** (0 111)	-0.7323*** (0.112)	-0.7292* (0.113)	-0.7263** (0.114)	-0.7230*** (0.115)	-1.4580* (2.967)
Three-Factor CAPM	-0.9563* (0.003)	-0.9532** (0.005)	-0.9509*** (0.007)	-0.9487* (0 009)	-0.9459** (0.010)	-1.9022* (5.382)	-0.9431*** (0.001)	-0.9399** (0.002)	-0.9369* (0.003)	-0.9343** (0.004)	-0.9310*** (0.005)	-1.8741* (4.783)
Four-Factor Carhart	0.4598* (0.191)	0.4575** (0.193)	0.4549** (0.195)	0.4520*** (0.197)	0.4491** (0.198)	-0.0107* (3.938)	0.4861** (0.110)	0.4835* (0.111)	0.4809*** (0.112)	0.4780* (0.113)	0.4754** (0.114)	-0.0107*** (4.893)
Four-Factor CAPM	-0.8680** (0.070)	-0.8651* (0.071)	-0.8628** (0.072)	-0.8597* (0.074)	-0.8568** (0.076)	-1.7248** (4.892)	-0.8994* (0.040)	-0.8967** (0.041)	-0.8941* (0.042)	-0.8909*** (0.043)	-0.8876** (0.044)	-1.7878* (5.783)
Five-Factor CAPM	-0 3481*** (0.011)	-0.3458* (0.013)	-0.3436** (0.014)	-0.3403* (0.015)	-0.3380** (0.016)	-0.6861* (5.835)	-0.3782** (0.012)	-0.3756* (0.014)	-0.3729*** (0.015)	-0.3700** (0.016)	-0.3671* (0.017)	-0.7452** (5.957)
Russia												
One-Factor CAPM	0.1470* (0.206)	0.1444** (0.207)	0.1411** (0.208)	0.1388* (0.209)	0.1359*** (0.210)	0.0111** (3.794)	0.1581** (0.107)	0.1551* (0.108)	0.1529*** (0.109)	0.1503* (0.110)	0.1483** (0.112)	-0.0098* (3.564)
Three-Factor CAPM	-0.3632** (0.169)	-0.3601* (0.170)	-0.3580*** (0.171)	-0.3556* (0.172)	-0.3529** (0.173)	-0.7161* (5.463)	-0.3327** (0.043)	-0.3305*** (0.044)	-0.3283** (0.045)	-0.3263** (0.046)	-0.3239* (0.047)	-0.6566* (4.463)
Four-Factor Carhart	0.5311** (0 129)	0 5288*** (0.130)	0.5266* (0.131)	0.5241** (0.132)	0.5226* (0.133)	-0.0085** (3.563)	0.6210*** (0.106)	0.6187* (0.107)	0.6166** (0.108)	0.6135* (0.109)	0.6112*** (0.010)	-0.0098* (4 463)
Four-Factor CAPM	-0 4354*** (0.005)	-0.4328* (0.006)	-0.4301** (0.008)	-0.4280** (0.010)	-0.4257* (0.012)	-0.8611** (3.463)	-0.4450*** (0.121)	-0.4428* (0.122)	-0.4407*** (0.123)	-0.4391*** (0.124)	-0.4374* (0.125)	-0.8824** (4.925)

Five-Factor CAPM	-0.6409* (0.124)	-0.6391** (0.125)	-0.6368*** (0.126)	-0.6342* (0.127)	-0.6326*** (0.128)	-1.2735* (3.783)	-0.8481*** (0.120)	-0.8458** (0.122)	-0.8432* (0.124)	-0.8403** (0.126)	-0.8372*** (0.128)	-1.6853** (3.957)
India												
One-Factor CAPM	-0.5261*** (0.071)	-0.5338** (0.072)	-0.5312* (0.073)	-0.05288*** (0.074)	-0.5259** (0.075)	-1.052* (3.782)	-0.2161*** (0.052)	-0.2138** (0.054)	-0.2113* (0.056)	-0.2084** (0.057)	-0.2052* (0.059)	-0.4213** (4.958)
Three-Factor CAPM	-0 7251** (0.113)	-0.7222* (0.014)	-0.7195*** (0.015)	-0.7169** (0.016)	-0.7146*** (0.017)	-1.4397* (4.846)	-0.5279*** (0.125)	-0.5258** (0.126)	-0.5239* (0 127)	-0.5218*** (0.128)	-0.5196** (0.129)	-1.0475** (6.463)
Four-Factor Carhart	0.2906*** (0.253)	0.2883** (0.255)	0.2854* (0.256)	0.2831** (0.257)	0.2816*** (0.258)	-0.0090* (4.846)	0.3606*** (0.100)	0.3583** (0.102)	0.3557* (0.104)	0.3532*** (0.106)	0.3501** (0.108)	-0.0105*** (4 707)
Four-Factor CAPM	-0.5702* (0.138)	-0.5689** (0.140)	-0 5666* (0.143)	-0.5638* (0.145)	-0.5616** (0.147)	-0.5564** (3.957)	-0.7230** (0.197)	-0.7215* (0.198)	-0.7192** (0.200)	-0.7170* (0.202)	-0 7145** (0.206)	-1.4475** (4.675)
Five-Factor CAPM	-0.1452** (0.177)	-0.1433* (0.178)	-0.1395** (0.179)	-0.1381* (0.180)	-0.1363** (0.182)	-0.2815** (4.784)	-0.4300*** (0.032)	-0.4281** (0.034)	-0.4262* (0.036)	-0.4243** (0.038)	-0.4225* (0.040)	-0.8525** (4.827)
China												
One-Factor CAPM	-0.1219** (0.11 7)	-0.1194* (0.119)	-0.1165** (0.120)	-0.1139* (0.121)	-0.1113** (0.123)	-0.2332*** (5.562)	-0.5425*** (0.172)	-0.5406** (0.174)	-0.5387*** (0.176)	-0.5358** (0.177)	-0.5339* (0.179)	-1.0764** (4.675)
Three-Factor CAPM	-0.2399** (0.219)	-0.2383*** (0.222)	-0.2364** (0 224)	-0.2335* (0.227)	-0.2304** (0.229)	-0.4703* (4.894)	-0.8743*** (0.071)	-0.8724** (0.073)	-0.8695** (0 075)	-0.8667*** (0.078)	-0.8634** (0.080)	-1.7377* (4.922)
Four-Factor Carhart	0.3199* (0.099)	0.3182** (0.102)	0.3155* (0.105)	0.3135** (0.108)	0.3112*** (0.114)	-0.0087* (6.353)	0.2618*** (0.180)	0.2606** (0.182)	0.2578* (0.184)	0.2550** (0.187)	0.2543* (0.191)	-0.0075** (3 967)
Four-Factor CAPM	-0.4207* (0.001)	-0.4188** (0.005)	-0.4175* (0.008)	-0.4154*** (0 015)	-0.4131** (0.019)	-0.8338** (4.784)	-0.5351* (0.043)	-0.5327** (0.046)	-0.5296* (0.049)	-0.5270*** (0.051)	-0.5242** (0.054)	-1.0593 (4.922)
Five-Factor CAPM	-0.9742*** (0.031)	-0.9716** (0.032)	-0.9687* (0.035)	-0.9664** (0.038)	-0.9637* (0.041)	-1.9379** (4.854)	-0.6819** (0.114)	-0.6788*** (0.118)	-0.6769* (0.120)	-0.6740** (0.125)	-0.6714* (0.128)	-1.3533** (4.674)
South Africa												
One-Factor CAPM	0.1257*** (0 151)	0.1241** (0.153)	0.1222* (0 155)	0.1206** (0.158)	0 1187* (0 161)	-0.0070** (3.883)	0.1131*** (0.127)	0.1112** (0.129)	0.1089** (0.131)	0.1062** (0.133)	0.1029* (0.136)	-0.0102*** (3.563)
Three-Factor CAPM	-0.2233* (0 212)	-0 2210** (0.215)	-0 2191*** (0.216)	-0.2172* (0 219)	-0 2139** (0.221)	-0.4372* (3.895)	-0.2103*** (0.129)	-0.2084* (0.130)	-0.2029** (0.133)	-0.2020* (0.135)	-0.2015** (0.137)	-0.4118** (3.672)
Four-Factor Carhart	-0.1190** (0.165)	-0.1175*** (0.168)	-0.1149** (0.170)	-0.1126** (0.173)	-0.1098*** (0.176)	0.2288** (4.538)	-0.5439*** (0.128)	-0.5416* (0.131)	-0.5397** (0.133)	-0.5374* (0.135)	-0.5348** (0.138)	-1.0787** (3.846)
Four-Factor CAPM	0.3282*** (0.227)	0 3258* (0 221)	0.3232** (0.227)	0.3201*** (0.229)	0.3191** (0.232)	-0.0091* (3.893)	0.6980*** (0.131)	0.6960** (0.132)	0.6933* (0.134)	0.6908** (0.137)	0.6883* (0.140)	-0 0097** (3.563)
Five-Factor CAPM	-0.7303*** (0.077)	-0.7278* (0.078)	-0.7248*** (0.080)	-0.7225** (0.083)	-0.7206* (0.087)	-1.4509** (3.743)	-0.4201*** (0.090)	-0.4182** (0.094)	-0.4151** (0.097)	-0.4124* (0.098)	-0.4101*** (0.101)	-0.0100* (3.893)

Note: The table presents the results of the JR puzzle. The full sample is divided into liquid and illiquid firms then these two groups are further divided into quintile portfolios of JR for all manufacturing firms of BRICS countries. Alpha is estimated using one factor to five factors CAPM models and presented along with their standard errors below in parentheses. ***, **, * shows the level of significance for 1%, 5%, and 10% respectively.

Table 4.19: Idiosyncratic Jump Risk Puzzle in Financially Constrained and Unconstrained Firms

	Financially Constrained Firms						Financially Unconstrained Firms					
Portfolios / Models	JR1	JR2	JR3	JR4	JR5	JR5-JR1	JR1	JR2	JR3	JR4	JR5	JR5-JR1
Pakistan												
One-Factor CAPM	0.5121** (0.003)	0.5102*** (0.005)	0.5084*** (0.007)	0.5071* (0.009)	0.5055** (0.010)	-0.0066* (3 785)	0.6855*** (0.029)	0.6832* (0.031)	0.6817** (0 033)	0.6794*** (0.036)	0.6771* (0.037)	-0.0084** (4.795)
Three-Factor CAPM	-0.3211*** (0.127)	-0.3188* (0.128)	-0.3169*** (0.129)	-0.3150** (0.130)	-0 3127*** (0.132)	-0.3295* (3.784)	-0.8895*** (0.040)	-0.8872** (0.041)	-0.8849* (0.042)	-0.8818** (0.045)	-0.8792* (0.047)	-1.7687** (11.785)
Four-Factor Carhart	-0.2890** (0.169)	-0.2871* (0.171)	-0.2850** (0.173)	-0.2834*** (0.175)	-0.2815* (0.179)	-0.5705** (4.995)	-0.6409** (0.160)	-0.6380* (0.162)	-0.6359** (0.164)	-0.6336*** (0.167)	-0.6307** (0.169)	-1.2716** (7.957)
Four-Factor CAPM	-0 3405** (0.012)	-0.3382*** (0.013)	-0.3353** (0 014)	-0.3330* (0.015)	-0.3307** (0.016)	-0.6712* (7.464)	-0.3545** (0.241)	-0.3524* (0.242)	-0.3501** (0.245)	-0.3475* (0.247)	-0.3452** (0.249)	-0.6997* (6.675)
Five-Factor CAPM	-0.5890* (0.210)	-0.5865** (0.211)	-0.5843*** (0.214)	-0.5821** (0.217)	-0.5799* (0.219)	-1.1689** (9.562)	-0.9367* (0.160)	-0.9338** (0.163)	-0.9309* (0.166)	-0.9288** (0.168)	-0.9267* (0.169)	1.8634* (8.673)
Brazil												
One-Factor CAPM	-0.1769* (0.011)	-0.1747** (0.013)	-0.1725*** (0.015)	-0.1703* (0.016)	-0.1681** (0.018)	-0.345* (6.453)	-0.7759** (0 012)	-0.7736* (0.015)	-0.7711** (0.017)	-0.7685*** (0.019)	-0.7662** (0.022)	-1.5421** (7.956)
Three-Factor CAPM	-0 4198** (0.107)	-0.4172*** (0.109)	-0.4143** (0.111)	-0.4117** (0.015)	-0.4088*** (0.017)	-0.8286** (6.845)	-0 1941** (0.222)	-0.1915** (0.226)	-0.1894* (0.228)	-0 1867** (0.230)	-0.1845*** (0.234)	-0.3786* (8.454)
Four-Factor Carhart	0.6219** (0.299)	0.6196** (0.301)	0.6174** (0.303)	0.6152** (0.305)	0 6130*** (0.307)	-0.0089** (3.574)	0.2161* (0.124)	0.2132*** (0.126)	0.2109** (0.127)	0.2080* (0.131)	0.2057** (0.137)	-0.0104* (5.674)
Four-Factor CAPM	-0.4197*** (0.022)	-0.4174** (0.025)	-0.4153* (0.026)	-0.4127** (0.027)	-0.4105* (0.021)	-0.8302** (7.453)	-0.5715*** (0.041)	-0.5689** (0.044)	-0 5660* (0.047)	-0.5631** (0.053)	-0.5602* (0.055)	-1.1317* (6.564)

Five-Factor CAPM	-0.7280** (0.160)	-0.7253* (0.162)	-0.7232** (0 165)	-0.7209*** (0.168)	-0.7109** (0.170)	-1.4389* (8.935)	-0.9931* (0.210)	-0.9902*** (0.213)	-0.9874** (0.218)	-0.9848* (0.222)	-0 9817*** (0.227)	-1.9748* (7.785)
Russia												
One-Factor CAPM	0.1203* (0.055)	0.1187** (0 057)	0.1163*** (0.061)	0.1145* (0.065)	0.1123** (0.068)	-0.0080* (5 896)	0.8939** (0.017)	0.8913*** (0.022)	0.8890* (0.024)	0.8865** (0.027)	0.8837*** (0.033)	-0.0102* (3.675)
Three-Factor CAPM	-0.2348** (0.011)	-0.2322*** (0.014)	-0.2301* (0.016)	-0.2288*** (0.021)	-0 2262* (0.025)	-0.461** (6.564)	-0.2600* (0.033)	-0.2571** (0.036)	-0.2545* (0.037)	-0.2751*** (0.043)	-0.2849** (0.044)	-0.5449** (4.565)
Four-Factor Carhart	0.3212** (0.011)	0.3186* (0.013)	0.3155** (0.016)	0.3129* (0.019)	0.3103** (0.020)	-0.0109* (0.563)	0.3622** (0.234)	0.3596* (0.235)	0 9579** (0.237)	0.3553* (0 239)	0.3524*** (0.240)	-0.0098** (3.000)
Four-Factor CAPM	-0.5418** (0.200)	-0.5392** (0.204)	-0.5369* (0.207)	-0.5343** (0.209)	-0.5317* (0.211)	-1.0735** (4.575)	-0.5545** (0.261)	-0.5518*** (0.263)	-0.5502* (0.264)	-0.5479** (0.265)	-0.5453* (0.266)	-1.0998** (5.675)
Five-Factor CAPM	-0.7400** (0.038)	-0.7384* (0.041)	-0.7357** (0.047)	-0.7328*** (0.050)	-0.7307** (0.053)	-1.4707* (8.574)	-0.7416* (0.202)	-0.7393** (0.205)	-0.7371* (0.208)	-0.7342** (0.210)	-0.732*** (0.211)	-1.4736* (6.6758)
India												
One-Factor CAPM	-0.9922* (0.156)	-0.9901** (0.157)	-0.9878* (0.158)	-0.9647** (0 160)	-0.9621* (0 162)	-1.9543** (12.674)	-0 9043** (0.241)	-0.9920* (0 242)	-0.897** (0.243)	-0.8963** (0.244)	-0.8640* (0.245)	-1.7683* (13.67))
Three-Factor CAPM	-0 7832** (0.012)	-0.7799*** (0.013)	-0.7778** (0.014)	-0.7752* (0.016)	-0.7726** (0.017)	-1.5558* (4.864)	-0.2540* (0.047)	-0.2514** (0.048)	-0.2488* (0.049)	-0.2457** (0.050)	-0.2439* (0.051)	-0.4979** (5.676)
Four-Factor Carhart	0.6890** (0.239)	0.6864* (0.240)	0.6838** (0.241)	0.6812* (0.243)	0.6779*** (0.245)	-0.0111** (6.675)	0.4969* (0.151)	0.4943** (0.153)	0.4917** (0.155)	0.4891* (0.156)	0.4874** (0.157)	-0.0095* (3.845)
Four-Factor CAPM	-0.3890** (0.075)	-0 3867* (0.077)	-0.3840** (0.079)	-0.3822*** (0 080)	-0.3801* (0.081)	-0.0769* (5.868)	-0.7848** (0.239)	-0.7821** (0.240)	-0.7792* (0.241)	-0.7759** (0.242)	-0.7733* (0.243)	-1.558** (5.758)
Five-Factor CAPM	-0.5999** (0.041)	-0.5973* (0.042)	-0.5950** (0.043)	-0.5921** (0.044)	-0.5898*** (0.046)	-1.1897** (9.676)	-0.3569** (0.059)	-0.3540* (0.060)	-0.3514*** (0.061)	-0.3496* (0 062)	-0.3475** (0.062)	0.7044* (6 756)
China												
One-Factor CAPM	-0.7540** (0.207)	-0.7517* (0 208)	-0.7496*** (0.209)	-0.7470* (0.211)	-0.7447** (0.213)	-1 4987* (6.867)	-0.7832** (0 002)	-0.7812*** (0.005)	-0.7790* (0.008)	-0.7772** (0 0012)	-0.7751*** (0 0017)	-1.5583* (11.384)
Three-Factor CAPM	-0.3890** (0.009)	-0 3857* (0.011)	-0.3827** (0.013)	-0.3806* (0.015)	-0.3781** (0.017)	-0.7671* (3.785)	-0.3340* (0.029)	-0.3322** (0.030)	-0.3301* (0.031)	-0.3284** (0.032)	-0.3272* (0.033)	-0.6612* (4.785)
Four-Factor Carhart	-0.5930** (0.030)	-0.5916*** (0.031)	-0.5893* (0.032)	-0.5871** (0.033)	-0.5848*** (0.034)	-1.1778** (6.565)	-0.6290** (0.018)	-0.6262*** (0.019)	-0.6244* (0.021)	-0.6227** (0.022)	-0.6209* (0.024)	-1.2499** (9.564)
Four-Factor CAPM	-0.6496** (0 233)	-0.6470* (0 234)	-0.6444*** (0 235)	-0.6423* (0.236)	-0 6401** (0.237)	-1.2897* (9.757)	-0.6713*** (0.139)	-0.6691** (0.140)	-0.6664* (0.141)	-0.6645** (0.142)	-0.6622* (0.144)	-1.3335** (9 673)
Five-Factor CAPM	-0.4330** (0.057)	-0.4304* (0.058)	-0.4283** (0.059)	-0 4257*** (0.060)	-0.4236* (0.061)	-0.8566* (9.675)	-0.4210* (0.247)	-0.4184*** (0.248)	-0.4160** (0.250)	-0.4137* (0.251)	-0.4111*** (0.253)	-0.8321* (7.564)

	South Africa											
One-Factor CAPM	0.1589** (0.190)	0.1566*** (0.191)	0.1537* (0.192)	0.1508** (0.194)	0.1475* (0.197)	-0.0114** (7.564)	0.1192*** (0.294)	0.1169** (0.297)	0.1148*** (0.301)	0.1135** (0.303)	0.1115*** (0.305)	-0.0077** (4.342)
Three-Factor CAPM	-0.3330* (0.105)	-0.3309** (0.106)	-0.3283* (0.108)	-0.3254** (0.110)	-0.3231*** (0.115)	-0.6561* (6.675)	-0.3138*** (0.030)	-0.3115* (0.032)	-0.3099** (0.033)	-0.3086* (0.034)	-0.3070** (0.035)	-0.6208* (6.956)
Four-Factor Carhart	-0.5934*** (0.209)	-0.5908** (0.210)	-0.5880*** (0.213)	-0.5875** (0.215)	-0.5834* (0.217)	-1.1768* (8.575)	-0.7653*** (0.047)	-0.7640** (0.050)	-0.7614** (0.053)	-0.7588*** (0.055)	-0.7562** (0.058)	-1.5215** (7.564)
Four-Factor CAPM	-0.7120** (0.107)	-0.7095*** (0.109)	-0.7082** (0.117)	-0.7069*** (0.118)	-0.7055** (0.1210	-1.4175* (11.786)	-0.8137*** (0.300)	-0.8124** (0.303)	-0.8112*** (0.307)	-0.8102** (0.310)	-0.8089* (0.314)	-0.0048* (1.045)
Five-Factor CAPM	-0.9210* (0.269)	-0.9184** (0.270)	-0.9169** (0.275)	-0.9150* (0.278)	-0.9124** (0.301)	-1.8334* (9.674)	-0.5140*** (0.019)	-0.5128** (0.021)	-0.5114*** (0.023)	-0.5099** (0.025)	-0.5086* (0.027)	-1.0226* (9.673)

Note: The table presents the results of the IR puzzle based on bivariate portfolio analysis. The full sample is divided into financially constrained and unconstrained firms then these two groups are further divided into quintile portfolios of IR for all manufacturing firms of BRICS countries. Alpha is estimated using one factor to five factors CAPM models and presented along with their standard errors below in parentheses. ***, **, * shows the level of significance for 1%, 5%, and 10% respectively.

Table 4.20: Idiosyncratic Jump Risk Puzzle in High, Medium, and Low Beta Firms

	High Beta Firms						Medium Beta Firms						Low Beta Firms					
Portfolios / Models	JR1	JR2	JR3	JR4	JR5	JR5-JR1	JR1	JR2	JR3	JR4	JR5	JR5-JR1	JR1	JR2	JR3	JR4	JR5	JR5-JR1
									Pakistan									
One-Factor CAPM	0.8120** (0.029)	0.8102*** (0.031)	0.8069* (0.034)	0.8056*** (0.035)	0.8043** (0.037)	-0.0077* (3.785)	0.9234** (0.257)	0.9211*** (0.261)	0.9175* (0.263)	0.9162*** (0.264)	0.9144** (0.267)	-0.0090** (8.271)	0.7210* (0.210)	0.7193** (0.213)	0.7174* (0.218)	0.7155** (0.222)	0.7132* (0.228)	- 0.0078* (3.628)
Three-Factor CAPM	-.7498*** (0.202)	-0.7475** (0.207)	-0.7457* (0.211)	-0.7441** (0.217)	-0.7422* (0.222)	-0.0076 (6.967)	-.2615*** (0.049)	-0.2592** (0.051)	-0.2559** (0.053)	-0.2543* (0.055)	-0.2525** (0.067)	-0.009 (5.071)	-0.4326* (0.035)	-0.4300** (0.037)	-0.4281* (0.040)	- 4263*** (0.045)	-0.4240** (0.047)	0.0112* (3.895)
Fou-Factor Carhart	-0.3900* (0.018)	-0.3874** (0.023)	-0.3851* (0.025)	- 0.3825*** (0.028)	-0.3806** (0.030)	-0.0094* (3.867)	-0.5730** (0.067)	-.5704*** (0.069)	-0.5671** (0.071)	-0.5656* (0.075)	-0.5638* (0.079)	-0.0092** (6.080)	-0.3893* (0.090)	-0.3867** (0.091)	-.3845*** (0.092)	-0.3819* (0.096)	-0.3800** (0.097)	- 0.0093* (3.785)
Four-Factor CAPM	-0.1863** (0.165)	-.1834*** (0.169)	-0.1811** (0.174)	-0.1789* (0.179)	-0.1767** (0.181)	-0.0096 (4.856)	-0.7800* (0.081)	-.7764*** (0.0830	-0.7738** (0.085)	-0.7720* (0.091)	-0.7704** (0.093)	-0.0096* (5..099)	-0.1933* (0.194)	-0.1917** (0.195)	-0.1898* (0.196)	- .1876*** (0.197)	-0.1843* (0.199)	-0.009* (5.946)
Five-Factor CAPM	-0.2780* (0.030)	-0.2747** (0.037)	-.2724*** (0.042)	-0.2711* (0.044)	-0.2685** (0.047)	-0.0095* (4.51)	-0.6213** (0.015)	-0.6197* (0.018)	-0.6174* (0.020)	-0.6151* (0.025)	-0.6132** (0.028)	-0.0081* (7.031)	-0.5733** (0.075)	-0.5697* (0.077)	-0.5666** (0.079)	-0.5650* (0.082)	-0.5634** (0.085)	- 0.0099* (4.856)

									Brazil									
One-Factor CAPM	-0.2769* (0.170)	-0.2736* (0.171)	-.2717*** (0.172)	-0.2619** (0.173)	-0.2658** (0.174)	-0.0111* (3.968)	-0.8759** (0.012)	-0.8736* (0.015)	-0.8711** (0.017)	-.8685*** (0.019)	-0.8662** (0.022)	-0.0097* (7.573)	-0.1759** (0.012)	-0.1736* (0.015)	-0.1711** (0.017)	- .1685*** (0.019)	-0.1662** (0.022)	- 0.0097* (3.895)
Three-Factor CAPM	-0.3197** (0.217)	-0.3164* (0.219)	-.3133*** (0.221)	-0.3107* (0.225)	-0.3086** (0.228)	-0.0111* (4.674)	-0.2941** (0.222)	-0.2915** (0.226)	-0.2894* (0.228)	-0.2867** (0.230)	-.2845*** (0.234)	-0.0096** (3.564)	-0.3941** (0.222)	-0.3915** (0.226)	-0.3894* (0.228)	- 0.3867** (0.230)	-.3095*** (0.234)	- 0.0846* (3114)
Fou-Factor Carhart	0.5219** (0.209)	0.5196* (0.210)	0.5183** (0.216)	0.5164* (0.218)	0.5148** (0.220)	- 0.0071** (3.957)	0.5161* (0.224)	0.5132*** (0.226)	0.5109** (0.227)	0.5080* (0.231)	0.5057** (0.237)	-0.0104* (1.674)	0.6161* (0.124)	0.6132*** (0.126)	0.6109** (0.127)	0.6080* (0.131)	0.6057** (0.137)	- 0.0104* (3.956)
Four-Factor CAPM	-.8197*** (0.022)	-0.8174** (0.024)	-0.8158** (0.026)	-0.8145* (0.027)	-.8124*** (0.031)	-0.0073* (7.947)	-.7715*** (0.041)	-0.7689** (0.044)	-0.7660* (0.047)	-0.7631** (0.053)	-0.7602* (0.055)	-0.0113* (8.564)	-.9715*** (0.141)	-0.9689** (0.144)	-0.9660* (0.147)	- 0.9631** (0.153)	-0.9002* (0.155)	- 0.0713* (6.463)
Five-Factor CAPM	-0.4280** (0.160)	-0.4247* (0.162)	-.4221*** (0.163)	-0.4203** (0.165)	-0.4187* (0.166)	-0.0093 (3.463)	-0.4931* (0.210)	-.4902*** (0.213)	-0.4874** (0.218)	-0.4848* (0.222)	-.4817*** (0.227)	-00085** (7.564)	-0.9931* (0.110)	-.9902*** (0.113)	-0.9874** (0.118)	-0.9848* (0.122)	-.9017*** (0.127)	- 0.0914* (5.891)
									Russia									
One-Factor CAPM	0.2803** (0.155)	0.2784** (0.157)	0.2765** (0.161)	0.2742* (0.0165)	0.2719*** (0.168)	-0.0084* (3.675)	0.3543** (0.030)	0.3520* (0.032)	0.3494** (0.035)	0.4371* (0.038)	0.3449** (0.041)	- 0.0094*** (0.746)	0.6971** (0.009)	0.6949* (0.011)	0.6926** (0.014)	0.6904* (0.017)	0.6881*** (0.021)	- 0.0090* (3.674)
Three-Factor CAPM	-0.5278** (0.111)	-0.5248* (0.114)	-0.5222** (0.116)	-0.5203** (0.121)	-0.5177* (0.125)	- 1.0455** (9.675)	0.8670* (0.072)	0.8644** (0.073)	0.8618* (0.075)	0.8595** (0.078)	0.8573* (0.081)	-0.0097* (1.785)	0.1452*** (0.053)	0.1426* (0.054)	0.1404** (0.056)	0.1403* (0.057)	0.1400*** (0.60)	- 0.0052* (3.896)
Fou-Factor Carhart	0.6412*** (0.211)	0.6396** (0.213)	0.6378* (0.216)	0.6352*** (0.219)	0.6329** (0.220)	-0.0083* (3.342)	0.1802*** (0.018)	0.1783** (0.021)	0.1757* (0.022)	0.1728*** (0.023)	0.1701* (0.025)	-0.0101** (1.957)	0.7800** (0.077)	0.7774* (0.078)	0.7748*** (0.080)	0.7722* (0.081)	0.7696** (0.083)	- 0.0104* (3.895)
Four-Factor CAPM	0.7320** (0.202)	0.7297* (0.203)	0.7271*** (0.204)	0.7242** (0.205)	0.7219*** (0.206)	- 0.0101** (4.56)	0.5987* (0.098)	0.5964** (0.099)	0.5942* (0.101)	0.5919** (0.104)	0.5896** (0.107)	-.0090*** (1.788)	0.4568* (0.045)	0.4542** (0.046)	0.4516* (0.048)	0.4487** (0.050)	0.4461* (0.053)	- .0107** (3.056)
Five-Factor CAPM	0.4409** (0.040)	0.4383 * (0.043)	0.4357*** (0.047)	0.4334** (0.050)	0.4301** (0.053)	-0.871** (4.686)	0.7801*** (0.082)	0.7778** (0.085)	0.7752* (0.087)	0.7731*** (0.091)	0.7705*** (0.093)	-0.0096* (1.784)	0.2654*** (0.027)	0.2628** (0.029)	0.2605*** (0.031)	0.2579* (0.033)	0.2553** (0.037)	- 0101** (3.785)
									India									
One-Factor CAPM	-0.1891** (0.106)	-0.1868** (0.107)	-0.1846* (0.108)	-0.1824** (0.109)	-0.1798* (0.110)	-0.3689* (4.785)	-0.2943** (0.041)	-0.2917* (0.042)	-.2894*** (0.043)	-0.2868** (0.044)	-0.2842* (0.045)	-0.5787 (4.564)	-0.8943** (0.004)	-0.8920* (0.006)	-.8889*** (0.007)	- 0.8863** (0.009)	-0.8840* (0.013)	- 1.7783* (4.878)
Three-Factor CAPM	-0.5832** (0.112)	- 0.5816*** (0.113)	-0.5794** (0.114)	-0.5778* (0.116)	-0.5795** (0.117)	-1.1627 (3.785)	-0.7540* (0.050)	-0.7514** (0.052)	-0.7488* (0.053)	-0.7457** (0.058)	-0.7439* (0.059)	-1.4953** (3.675)	-0.6544* (0.247)	-0.6518** (0.248)	-0.6492* (0.249)	- 0.6466** (0.250)	-0.6437* (0.251)	- 1.2981* (4.851)
Fou-Factor Carhart	0.6810** (0.139)	0.6784* (0.140)	0.6758** (0.141)	0.6737* (0.143)	0.6715*** (0.145)	- 0.0095** (3.785)	0.8960* (0.251)	0.8943** (0.253)	0.8917** (0.255)	0.8891* (0.256)	0.8874** (0.257)	-0.0086* (3.861)	0.3960* (0.156)	0.3934** (0.157)	0.3909** (0.158)	0.3884* (0.159)	0.3857** (0.161)	- 0.0103* (5.898)
Four-Factor CAPM	-0.8890** (0.275)	-0.8868* (0.277)	-0.8847** (0.279)	-.8824*** (0.280)	-0.8798* (0.281)	-1.7688* (3.968)	-0.5848** (0.240)	-0.5821** (0.242)	-0.5792* (0.243)	-0.5759** (0.244)	-0.5733* (0.245)	1.118** (3.785)	-0.1849** (0.239)	-0.1823** (0.242)	-0.1797* (0.244)	- 0.1770** (0.248)	-0.1747* (0.249)	-0.3596 (1.786)
Five-Factor CAPM	-0.7999** (0.141)	-0.7976* (0.142)	-0.7950** (0.143)	-0.7950** (0.144)	-.7924*** (0.146)	-1.5923 (6.685)	-0.4569** (0.059)	-0.4540* (0.060)	-.4514*** (0.061)	-0.4496* (0.062)	-0.4475** (0.062)	0.9044* (3.785)	-0.7560** (0.189)	-0.7534* (0.191)	-.7507*** (0.193)	-0.7478* (0.195)	-0.7449** (0.197)	- 1.5009* (1.786)

China																		
One-Factor CAPM	-0.8546** (0.107)	-0.8520* (0.112)	-.8504*** (0.114)	-0.8478* (0.117)	-0.8450** (0.121)	1.6996 (9.786)	-0.2647** (0.131)	-0.2620* (0.132)	- 0.2593*** (0.133)	-0.2567* (0.134)	-0.2538** (0.135)	-0.5185** (3.786)	-0.3849** (0.213)	-0.3823* (0.216)	- 0.3790*** (0.220)	-0.3759* (0.225)	-0.3733** (0.228)	- 0.7582* (3.674)
Three-Factor CAPM	-0.1893** (0.015)	-0.1866* (0.018)	-0.1837** (0.023)	-0.1803* (0.027)	-0.1785** (0.032)	-0.3678 (3.897)	-0.5795** (0.091)	-0.5769* (0.092)	-0.5740** (0.093)	-0.5712* (0.094)	-0.5686** (0.095)	-1.1481* (4.786)	-0.7230** (0.020)	-0.7207* (0.027)	-0.7186** (0.032)	-0.7170* (0.036)	-0.7144** (0.040)	- 1.4374* (4.786)
Fou-Factor Carhart	-0.5938** (0.035)	-.5912*** (0.038)	-0.5885* (0.042)	-0.5858** (0.045)	-.5830*** (0.044)	-1.1768* (4.675)	-0.6687** (0.036)	-.6662*** (0.038)	-0.6638* (0.044)	-0.6610** (0.047)	-.6581*** (0.051)	-1.3268** (4.897)	-0.4931** (0.072)	-.4903*** (0.075)	-0.4874* (0.078)	- 0.4851** (0.083)	-.4825*** (0.085)	- 0.9756* (3.896)
Four-Factor CAPM	-0.9496** (0.033)	-0.9470* (0.034)	-.9444*** (0.035)	-0.9423* (0.036)	-0.9397** (0.037)	-1.9193 (5.786)	-0.8490** (0.053)	-0.8470* (0.054)	-.8444*** (0.055)	-0.8423* (0.056)	-0.8401** (0.057)	-1.6891 (5.786)	-0.1490** (0.230)	-0.1470* (0.235)	-.1444*** (0.238)	-0.1423* (0.242)	-0.1401** (0.247)	- 0.2891* (3.685)
Five-Factor CAPM	-0.4320** (0.067)	-0.4297* (0.068)	-0.4271** (0.069)	-.4241*** (0.070)	-0.4215* (0.071)	-0.8535* (0.342)	-0.3350** (0.065)	-0.3304* (0.068)	-0.3283** (0.073)	-.3257*** (0.078)	-0.3236* (0.085)	-0.6586* (5.967)	-0.5339** (0.050)	-0.5304* (0.053)	-0.5283** (0.058)	-0.525** (0.063)	-0.5236* (0.065)	-.0575* ((8.675)
South Africa																		
One-Factor CAPM	0.2567** (0.195)	0.2550*** (0.198)	0.2537* (0.112)	0.2508** (0.118)	0.2475* (0.122)	-.0092** (3.675)	0.5298*** (0.007)	0.5269** (0.013)	0.5248*** (0.018)	0.6135** (0.022)	0.5215*** (0.025)	-0.0083** (3.785)	0.6568*** (0.095)	0.6560** (0.097)	0.6540*** (0.099)	0.6525** (0.102)	0.6518*** (0.104)	-0005** (3.629)
Three-Factor CAPM	-0.7370* (0.024)	-0.7309** (0.026)	-0.7283* (0.028)	-0.7254** (0.031)	-.7231*** (0.036)	- 1.4501** (5.675)	-.3830*** (0.031)	-0.3815* (0.033)	-0.3789** (0.034)	-0.3756* (0.035)	-0.3730** (0.036)	-0.756** (4.675)	0.9198*** (0.030)	0.9170* (0.033)	0.9155** (0.034)	0.9130* (0.035)	0.9115** (0.036)	-0.008* (3.906)
Fou-Factor Carhart	-.6934*** (0.209)	-0.6908** (0.210)	-.6880*** (0.213)	-0.6861** (0.215)	-0.6834* (0.217)	- 1.3768** (8.674)	-.4656*** (0.047)	-0.4640** (0.050)	-0.4614** (0.053)	-.4588*** (0.055)	-0.4562** (0.058)	-0.9218* (3.867)	-.3853*** (0.047)	-0.3840** (0.050)	-0.3814** (0.053)	-.378*** (0.055)	-0.3762** (0.058)	- 0.761** (7.906)
Four-Factor CAPM	-0.5320** (0.101)	0.5294*** (0.109)	-0.5284** (0.117)	-0.526*** (0.118)	-0.5250** (0.121)	-.007*** (4.785)	-0.763*** (0.300)	-0.7624** (0.303)	-0.761*** (0.307)	-0.7600** (0.310)	-1.523** (3.314)	-0.0050** (3.705)	-0.443*** (0.300)	-0.4424** (0.303)	-0.441*** (0.307)	0.4380** (0.310)	--0.4360* (0.314)	- 0.879** (3.675)
Five-Factor CAPM	-0.9710* (0.269)	-0.9684** (0.270)	-0.9669** (0.275)	-0.9650* (0.278)	-0.9624** (0.301)	-0.008** (3.785)	-0.114*** (0.019)	-0.1128** (0.021)	-0.111*** (0.023)	-0.1099** (0.025)	-0.1080* (0.027)	-0.222** (3.786)	-0.724*** (0.019)	-0.7228** (0.021)	-0.721*** (0.023)	-0.718** (0.025)	-0.7156* (0.027)	-.439** (5.897)

Note: The table presents the results of the JR puzzle based on bivariate portfolio analysis. The full sample is divided into high, medium, and low beta firms. Then, these three groups are further divided into quintile portfolios of JR for all manufacturing firms of BRICS countries. Alpha is estimated using one factor to five factors CAPM models and presented along with their standard errors below in parentheses. ***, **, * shows the level of significance for 1%, 5%, and 10% respectively.

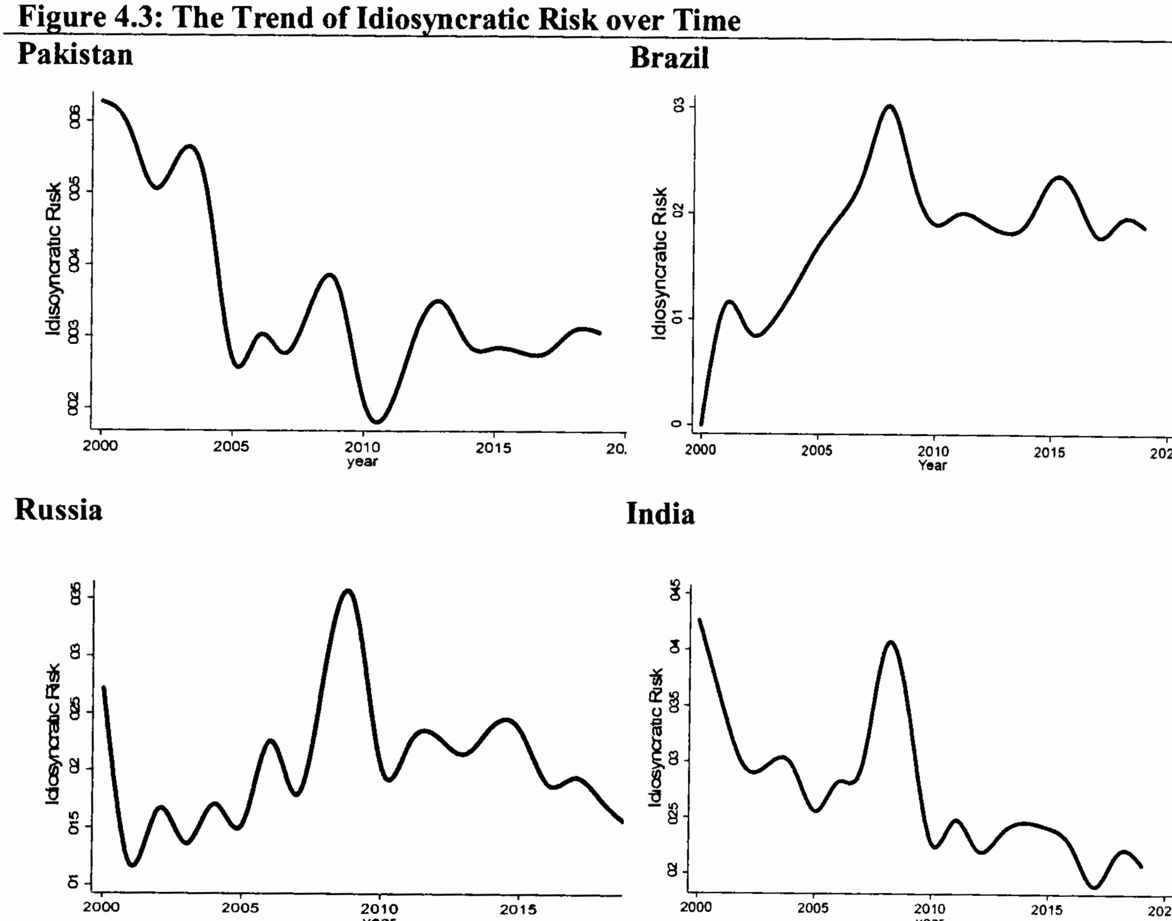
Although all type of beta-based groups of firms shows the JR puzzle, for some specific CAPM models, the alpha values of JR5 have high negative values for high-beta firms compared to low- and medium-beta group of firms. In all cases we observe that the estimated alpha are statistically different from 0, at conventional levels, in a relevant number of regressions and that their values are also large and negative. Since the alpha values or average return is significantly different from zero and on average negative and statistically significant. As low and high expected jump portfolios are formed, respectively, by assets with negative and positive expected jump component, the observation of a negative mean monthly jump returns return indicates that assets with negative expected jump present lower returns. These findings are against with the possible explanation by considering the concepts of loss aversion and probability weighting in the field of prospect theory (see among others Kahneman and Tversky (1979), Barberis and Thaler (2003), and Barberis (2013)). Indeed, investors show greater sensitivity to large negative expected jumps and overweight low probabilities, pushing them to demand an insurance over large negative expected jumps.

Further, emerging markets are comparatively less efficient than developed markets that is why occurring of jumps in emerging markets are more frequently. The jump puzzle findings are consistent with the studies of Zada, Arshad, & Wong (2021). They documented that emerging equity markets are more exposed due to jump risk comparatively developed equity markets. They also documented that merging markets are more exposed due to volatility during the periods of negative jumps. In addition, jimp-based volatility is the major part of the realized volatility. Therefore, Integrated volatility is high during periods of negative jump and this pattern is similar for developed and emerging markets.

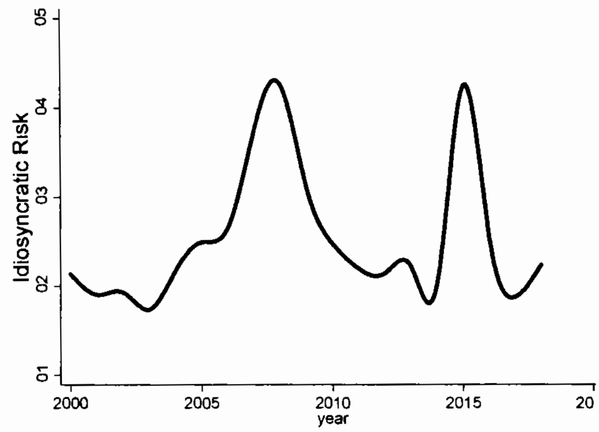
4.11. Idiosyncratic Risk and Idiosyncratic Tail Risk over Time

Figure 4.3 presents a visual trend of IR series over time for all sample countries BRICS and Pakistan. These series do not show any significant trend. Although IR is high in the starting years for Pakistan, India, Russia and South Africa.

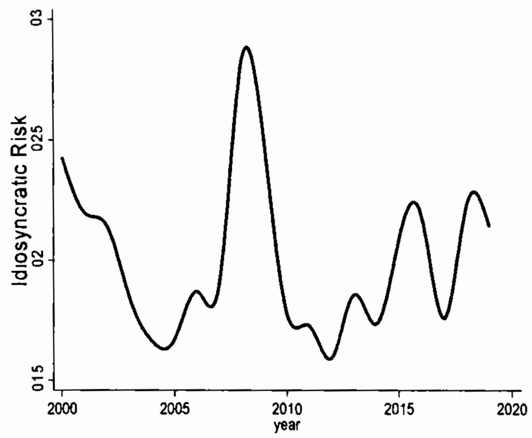
Figure 4.3: The Trend of Idiosyncratic Risk over Time



China



South Africa

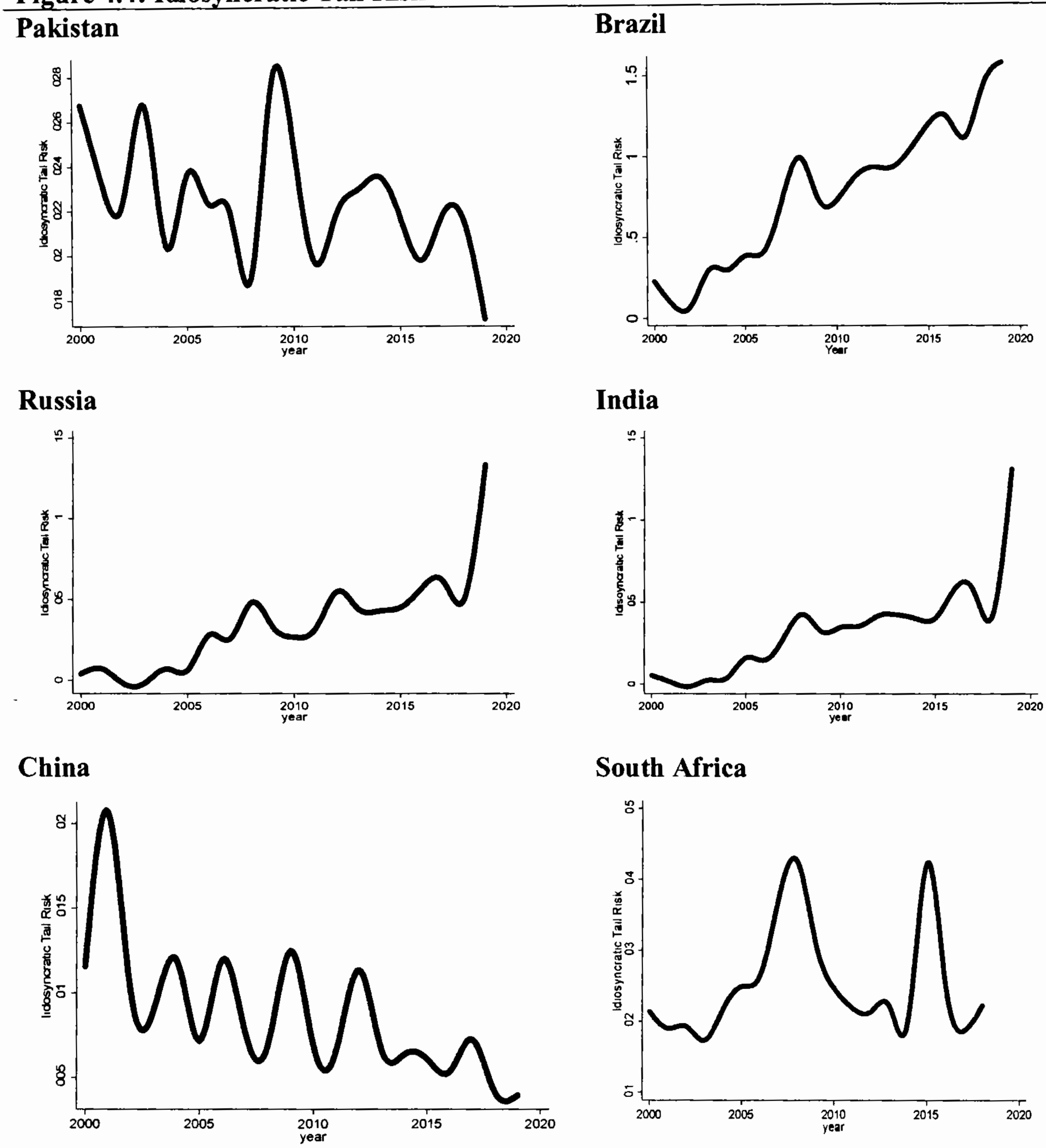


Note: The figure shows the graphical represent for the trend of idiosyncratic risk

Generally, there is no systematic and common pattern appears for all graphs. However, the common peak was evident for the year 2008. This reveals that during the financial crisis of 2007/8, the trend of IR shows a high peak. Overall, there is less volatility observed for India, and quite a stable trend has been observed for Pakistan in recent years. There is a decreasing trend observed for all countries except China. As China shows an upward trend of IR.

Figure 4.4 shows the trend of idiosyncratic tail risk (left tail) over time for the considered sample. For the developing country Pakistan, we can over that there are decreasing patterns shows. However, all BRICS member countries show an upward trend except China. The ITR is decreasing over time for China, and in near 2019, it will become an upward trend. One common pattern in all graphs is that around 2008, the ITR is high in all sampled countries. There is also evidence of countercyclical behavior of the IR for China and Pakistan.

Figure 4.4: Idiosyncratic Tail Risk



Note: The figure shows the graphs that represent the trend of idiosyncratic tail risk

Chapter 5
Conclusion

5.1. Introduction

The final chapter provides a review and brief discussion of the results. Some concluding remarks are presented, and we provide suggestions for future research in the following sections. This study considers unbalanced panel data on all nonfinancial firms listed on the major stock exchanges of BRICS countries and Pakistan, namely, the Shanghai Stock Exchange (China), National Stock Exchange (India), Johannesburg Stock Exchange (South Africa), Sao Paulo (Brazil), Moscow Stock Exchange (Russia) and Pakistan Stock Exchange (Pakistan). The study covers the period from 2000 to 2019. The core objective of this study is to examine the IR, ITR, and JR puzzles overall and in different groups of firms for top emerging countries, such as the BRICS and developing country Pakistan.

Our first objective is to explore the IR puzzle. For this, we examine the IR and stock returns relationship. To examine the IR puzzle, we apply different parametric (t-test, asset pricing models, portfolios analysis) and non-parametric (stochastic dominance, quantile regression) techniques and portfolio analysis to explore and confirm the existence of the IR puzzle.

Our second objective is to explore the IR puzzle in different groups of firms. We have divided the firms based on their fundamental characteristics, such as liquid and illiquid, financially constrained, and financially unconstrained. In these groups of firms, we further divided the firms into five quantiles of idiosyncratic risk portfolios and applied one- to five-factor asset pricing models.

Our third objective is to find the empirical determinants of IR. We apply static (the fixed effect model) and dynamic (the GMM model) panels. The same objective is achieved in firms by dividing them into their fundamental characteristics.

Our fourth and fifth objectives are to propose a pricing factor for IR and check that this pricing factor plays a significant role in IR pricing in the equity market. For this, we have constructed a modified arbitrage score factor based on different firm fundamental and behavioral factors and made a factor and added it into the five-factor Fama and French CAPM model to check whether the IR is priced in the stock market. In other words, we extend the analysis in asset pricing models to examine the pricing of a potentially hidden non-diversifiable factor.

Our sixth objective is to explore the ITR puzzle. For this, we examine the relationship between ITR and stock returns and show the existence of an ITR puzzle in the sample countries. In-depth analysis, we examine the relationship between upper and lower tail risks with stock returns.

Our seventh objective is to explore the JR puzzle. We examine the relationship between positive and negative jumps with the stock returns.

Our eighth objective is to examine the ITR and JR puzzle in different groups of firms divided into their liquidity positive, systematic risk, and financial constraints. Finally, we do a graphical analysis to examine the IR and ITR trends. Following are the sub-sections of this chapter.

5.2. Key Findings

This study answers several inconclusive questions associated with idiosyncratic risk and stock returns. For instance, the findings related to IR show strong evidence of the idiosyncratic risk puzzle in all emerging countries of BRICS and developing country Pakistan, as the stock returns are significantly and negatively related to IR. Consistent with arbitrage asymmetry, this negative relation in high beta, illiquid, and financially constrained stocks is more substantial and statistically significant than their counterpart firms. Based on the parametric and non-parametric tests, the analysis produced significant, consistent results with only the literature supporting the IR puzzle: IR and stock returns have a negative relationship.

We have applied different parametric and non-parametric approacher to examine the confirm the IR puzzle. The findings based on asset pricing models show that the results for Russia, India, and China show negative alpha values that, in some places, decrease monotonically from the lowest IR to the highest IR quintile portfolios. The difference in the alpha values among the one- to five-factor CAPMs is statistically significant, at least at the 5 percent level. However, the results of the Carhart model are somewhat mixed. For instance, Russia has a weak indication of the IR puzzle only for the first and second quintiles of IR. Although the remaining alpha values are declining, they are not statistically significant. Similarly, the alpha values estimated with the Carhart model show a weak indication of the IR puzzle in India. No evidence of the IR puzzle is found in China.

The findings of stochastic dominance provide clear evidence that the high IR-based and small-size portfolios both give lower returns than their counterpart portfolios. This evidence confirms the presence of an IR puzzle. The results indicate the presence of IR puzzle hold for all the BRICS member countries and Pakistan.

The result for quantile regression shows that the slope coefficient of IR is negative and significant from the 20^{th} to 80^{th} quantiles, including OLS estimates for India and China and developing country Pakistan. In contrast, the slope coefficients of Brazil, Russia, and South Africa are negative at lower quantiles and become positive at upper quantiles. Specifically, we can observe that the high coefficient of IR decreases with the stock returns. These results hold for all sample countries except Russia. For instance, Russia is the only country where the IR puzzle is observed for 20 percent of stock returns. The IR puzzle is found in the remaining sample countries from the 20^{th} to the 80^{th} quantiles.

Move towards the findings of the IR puzzle in different groups. There is no substantial evidence for liquid firms favoring the IR puzzle. For instance, no evidence exists in India and South Africa liquid firms. For China, we find that the IR puzzle exists with one- and five factors, and in Brazil, only with the one-factor CAPM model. However, no evidence is found for Russia. The results of illiquid firms indicate that, on average, alpha values are very significant and have systemically declining patterns in the multifactor regressions for each country, from the lowest to the highest IR. Alternatively, when IR rises, the abnormal return performance of the illiquid firms falls, indicating a negative relationship between stock returns and the IR.

Based on financial constraints, confirm that the average return for FC firms poses a challenge to existing empirical asset pricing models. In other words, the alpha values of FC firms are nonzero and statistically significant. Remarkably, abnormal performance (alpha) is the lowest in IR5 portfolios in Brazil, Russia, and India for all the estimated models (the one- to five-factor models and the Carhart model). But in China, the alpha values are lowest for the one-, two-, and five-factor CAPM models. Similarly, South Africa's lowest value is found only with the five-factor CAPM model.

The results for FUC firms also have similar results to some extent. For example, the IR puzzle exists in all asset pricing models except the Carhart model. In Russia, the puzzle is evident for all models except the one-factor CAPM model. We found mixed evidence for the IR puzzle in India, China, and South Africa. However, based on a comparison of alpha values, we can conclude that financially constrained firms experience higher sensitivity to IR than more financially constrained firms. On average, the less financially constraints alphas for IR5 are high for all BRICS countries. The spread between IR5 and IR1 in all capital asset pricing models is highly significant. Consequently, the GRS test strongly rejects the null hypothesis that alphas are zero, regardless of the asset model employed. In other words, the portfolio of the most financially constrained firms slightly underperforms the less constrained firms, thus providing evidence of the IR puzzle.

The finding based on systematic risk shows that the results for Brazil show the existence of the IR puzzle for high-beta firms in all the asset pricing models. However, we find mixed results for medium- and low-beta firms, indicating the presence of the IR puzzle; that is, the alpha values of the IR5 portfolios are higher than IR1. The IR puzzle is evident in high- and medium-beta firms in India, China, and South Africa. This implies that high-beta firms are generally less diversified and, thus, more sensitive to IR. Further, the results of high- and low-beta firms have a systemic pattern from the IR1 to the IR5 portfolios. This implies that from the lowest to the highest IR portfolios, the alpha values of all the estimated asset pricing models decrease and are statistically significant.

This puzzle has two potential explanations. The first explanation concerns biased beliefs. Biased beliefs are the drivers for several mispricing, and such beliefs tend to be more vital in developing and emerging markets. Therefore, biased beliefs may also drive the difference in the effects of idiosyncratic risk on pricing in emerging markets. Market-wide sentiments and their variations significantly affect the appearance and magnitude of market anomalies. The variations in market-wide investor sentiment have meaningful effects on the appearance and magnitude of anomalies, and these sentiments induce demand shocks from institutional investors. Many sentiment-induced demand shocks come from institutional investors rather than individuals. In addition, institutional investors are more likely to buy overvalued stocks and become the critical culprits in producing asset-pricing anomalies.

The results for determinants of idiosyncratic risk show that firm size, leverage, market power, liquidity, return on equity, price-to-earnings ratio, and dividend yield are the significant determinants of the idiosyncratic risk of all manufacturing and different categories of firms across all considered countries of BRICS and Pakistan. However, momentum return has the predictive power to explain the idiosyncratic risk for the sample countries having significantly positive and negative signs. The findings are robust when controlling the firm size. The findings suggest that these firm-specific variables are the significant determinants of the idiosyncratic risk and support the under-diversified portfolio theory.

The findings related to IR pricings, we have found that the arbitrage score significantly impacts the stock returns throughout the sample countries. Said differently, the arbitrage score factor is economically and statistically significant and positively affects stock returns in BRICS' equity markets. These results support using the arbitrage score as a proxy for relative stock mispricing. These results confirm that the CAPM probably leaves out non-diversifiable factor(s) in its specification, and similarly, the same issue is observed for using the Fama-French models. Therefore, it is advisable to proclaim the inclusion of IR in asset pricing models.

Overall, we can observe that the coefficient values of the ITR have consistently negative signs and tend to decrease with the increase in the quintile of stock returns. In other words, the coefficient values of ITR from the low to high quintile of stock returns tend to decrease monotonically. Thus, we can conclude that through quintile regression, we find an "idiosyncratic tail risk puzzle" or a negative effect of idiosyncratic tail risk toward stock return in all BRICS, including the Pakistani equity market. In-depth analysis, we find that in the 20% or lowest quantile, the magnitude of this negative relationship is large for China and India compared to their counterpart countries. However, although for 80% quantile, the magnitude for Pakistan, Brazil, and South Africa is not large but has a significant effect. The results show that ITR has a statistically negative coefficient for all sample countries, showing that the ITR puzzle exists in all emerging and Pakistani equity markets.

Further, when we compare the relationship between ITR and stock returns based on liquid and illiquid firms, we can conclude that the illiquid firms' group is more exposed due to the high level of ITR. Said differently, when both liquid and illiquid firms are considered, the illiquid type has considerably higher exposure due to ITR than the other. In contrast, in India, the intensity of ITR puzzle existence in liquid firms high than in illiquid firms. The findings for China and South Africa show similar results: illiquid firms are more exposed to the ITR puzzle in one-factor, three-factors, and four-factor CAPM models.

Based on financial constraints, the results for Pakistan specifically show that the exposure (negative alpha values) or the negative effect of ITR is more intense for the FUC group for all the CAPM and Carhart models except the one-factor CAPM model. When we discuss the exposure of ITR in emerging countries, we cannot see a clear pattern of which group is more affected. However, we can say that the intensity of the ITR puzzle is high, mainly in the FUC group of firms, while considering the alpha values of ITR5 portfolios. Said differently, abnormal performance (alpha) is the lowest in ITR5 portfolios in the BRICS countries mostly. Notably, the alpha values for ITR5 in Brazil show evidence of the ITR puzzle in all CAPM models except in three-factor CAPM. For Russia, there is also a strong tendency to the existence of an ITR puzzle in all CAPM models except in the four-factor Carhart model.

There are mixed findings favoring the ITR puzzle based on systematic risk. However, there is no indication of the ITR puzzle in using one-factor CAPM for the Pakistan and South Africa case and the four-Carhart model for Brazil, Russia, and India. The remaining CAPM models' findings show mixed findings favoring the ITR puzzle in sample countries. For instance, the findings of Pakistan, Brazil, and India show that the ITR puzzle is more stressful for high-beta firms than their counterparts for some CAPM models. As we can observe, the alpha values of ITR5 for high-beta firms show worse performance in terms of returns. This implies that high-beta firms institutively are the risky firms, which is why their returns relationship with their ITR is also worse as increase the ITR.

Similarly, in some CAPM models, the ITR puzzle intensity in low-beta firms is high. The possible justification for the negative relationship between tail risk and stock returns was given by Fang, Ruan, & Zhang (2020). They documented that stocks in emerging countries are more sensitive to left-tail risk than developed stock markets, and stocks with high tail risk have subsequent low returns.

The findings related to the JR puzzle are based on the quantile regression results, and we found interesting results favoring the JR puzzle. JR's coefficient values decrease from 20% to 80% quantile and have a significant negative relationship with their stock returns at any acceptable significance level. These findings support our hypothesis that high negative jumps earn lower returns than their counterpart. Interestingly, these results are similar for all sample countries. However, a 20% quantile, positive and insignificant relationship is found between JR and stock returns. The coefficients for JR remain highly significant after controlling for all conventional risk factors, and JR plays a significant role in the expected returns.

Comparing the country vice JR exposure on stock returns, we can observe that the difference column JR5-JR1 for FC firms is statistically high for Pakistan, Brazil, and

Russia. On the other hand, there is evidence of the JR puzzle for India, China, and South Africa, but we cannot distinguish the intensity of JR exposure based on groups. Said differently, no systematic pattern exists of JR exposure in FC and FUC firms. In some CAPM models, JR's intensity is higher in FC firms than in their counterpart firms.

The findings of the JR puzzle related to market risk show the JR puzzle exists in low-, medium-, and high-beta-based firms. For Pakistan, high-beta firms show more exposure due to JR as alpha values for JR5. The difference column JR5-JR1 shows negative and statistically significant performance compared to their counterparts. When we observe the alpha values of JR5 for the emerging countries, we cannot clearly state that any specific group of firms has high exposure due to JR.

Our findings are consistent with the studies done by Tariq, Abbas, & Rashid (2022). They have documented the impact of jump-diffusion components of volatility and realized jump. They then examined this impact on the aggregate stock returns of emerging and developing countries. Because when there are negative jumps, there is an indication of losing share in terms of returns by the firms. In general, although the results vary based on the analysis we used. However, the differences are only based on the magnitude and intensity. The main justification is that the macroeconomic factors may change the country to country and market and country-specific factors my differently impact on the considered puzzle in my thesis.

5.3. Policy Implications and Recommendations

Based on this study, it is possible to establish several expected policies. For example, financial managers should also consider stock price fluctuations to establish diversification policies. It also explains that asset managers can closely differentiate between hedging approaches, for instance, ex-ante and ex-post. Furthermore, tail risk measure derived from returns has predictive power for future aggregate market returns and a cross-section of stock returns. The tail risk significantly contributes to a better understanding of the theories of market efficiency.

Regulatory authorities are responsible for maintaining the efficiency of capital markets, so this study will also assist these bodies. For example, evidence of IR, JR, and ITR puzzle helps government and security regulations to implement their policies. They forbid access to private information. After detecting these puzzles, companies would be well advised and instructed to follow the rules of the SECP and give an indication in their financial reporting of such puzzles and anomalies. Due to the potential for manipulation and irrational stock trading, a lack of confidence in equity markets, highlighted by repeated scandals, scams, and speculative behaviour, entails costs for market participants and increases financial intermediation costs. Security organizations can also use this information to predict more accurately and provide better recommendations to improve investor understanding. Additionally, it is advised that when lawmakers make such laws and regulations in these financial markets, they protect brokers' investments by preventing them from negatively impacting stock market speculation.

Through this study, financial practitioners will get help understanding investors' decision-making, and they can justify the stock returns. As a result, the stock price will reflect its fundamental value. Pakistan's stock market will become the yardstick of the economy's health and help businesses enhance their production and capital. Furthermore, the current study of extreme events such as tail and JR suggests that regulators should be concerned with excessive volatility, reflecting other factors such as potential market manipulation and speculative trading.

Moreover, these findings may have direct implications for investors sensitive to idiosyncratic risk, fund managers, and researchers interested in idiosyncratic risk determinants. China appears to be the most influential country globally among the BRICS member countries. Therefore, it seems very likely that the other BRICS economies will eventually become more integrated into the increasingly influential Chinese economy concerning trade, foreign direct investment flows, and migration. This avenue of firm-specific risk avoidance for international financial investors may correspondingly diminish. Therefore, it is not wrong to say that BRICS can be considered a destination for portfolio diversification globally.

With these mixed and nonlinear results of the jump-diffusion phenomenon, realised jumps, and stock returns, it is difficult to formulate a clear policy. However, based on these findings, financial managers and investors can build diversified portfolios by selecting sectoral firms that have positively responded to realised jumps and jump-diffusion components of volatility in a variety of market conditions. Financial managers may also consider other factors related to improved firm characteristics and market, which will help in portfolio growth and investment returns.

5.4. Limitations of the Study

The study has some limitations in terms of scope and application.

- We limit our dataset to include top emerging BRICS countries and developing countries like Pakistan.

- The study considers only the firm-specific variables to examine the IR, JR, and ITR puzzle. The study ignores the corporate governance variables.
- This study only used three-factor Fama and French CAPM to estimate the IR. IR can be estimated through the EGARCH model and compare the results for robustness.

5.5. Direction for Future Research

- Further research can be done using other divisions of firms, such as hi-tech firms, based on capitalization and industries.
- Such analysis can also be carried out on South Asian stock markets. Further, the generalization of our findings can be confirmed by doing such a type of analysis for developed, developing, and emerging economies.
- A wider sample will provide a better opportunity to compare the findings as there is the possibility that the determinants of the idiosyncratic risk may differ across different categories of countries.
- Alternative IR measures might be carried out to provide a thorough understanding of IR in the stock market. This might entail measuring IR using the EGARCH approach, and the outcomes can be compared to our findings.
- In further research, the study can be done by investigating the firm's qualitative components and understanding their implications in relation to firm-specific risks.
- Finally, an interesting topic for practitioners would be to closely examine the role of investor sentiment in reconciling the relation between stock returns and IR. We

suggest testing the IR behaviour during high investor sentiment compared to low sentiment periods.

- Most importantly, future studies could also incorporate jumps as a factor in asset pricing models.

"In my end, it is my beginning" (T.S. Eliot)

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Appendix

Appendix Table III: Robustness Tests

	Model 1		Model 2	
Brazil				
Variables	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**
Constant	0.038**	0.145	0.027*	0.040
Firm Size	-0.049**	0.039	-0.007**	0.150
Leverage	0.028*	0.136	0.015*	0.038
Market Power	-0.014**	0.024	-0.028**	0.071
Liquidity	0.054**	0.084	0.021**	0.070
Momentum Return	0.379***	0.039	0.159**	0.215
Return on Equity	-0.155**	0.023	-0.146*	0.012
Price to Earnings ratio	-0.188*	0.019	-0.117**	0.424
Dividend Yield	-0.077***	0.033	-0.061**	0.063
R-squared	0.115		0.149	
Number of obs	2822		2821	
F-test	9.568		6.957	
Prob > F	0.001		0.001	
Hausman Chi-square test value	23.787		45.896	
P-value	0.000		0.002	
Russia				
Variables	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**
Constant	0.020***	0.029	0.030***	0.088
Firm Size	-0.064***	0.010	-0.094***	0.030
Leverage	0.021*	0.025	0.026***	0.083
Market Power	.-0.012**	0.027	-0.049***	0.090
Liquidity	0.372**	0.072	0.784***	0.023
Momentum Return	0.030**	0.040	0.081***	0.013
Return on Equity	-0.017*	0.040	-0.013***	0.013
Price to Earnings ratio	-0.073***	0.030	-0.093***	0.102
Dividend Yield	-0.016*	0.049	-0.050***	0.016
R-squared	0.132		0.167	
Number of obs	7500		6999	
F-test	17.14			
Prob > F	0.000		0.000	
Hausman Chi-square test value	9.574		7.584	
P-value	0.001		0.023	
India				
Variables	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**
Constant	0.034**	0.021	0.013***	0.011
Firm Size	-0.057**	0.213	-0.036**	0.012
Leverage	0.021 *	0.021	0.070*	0.024
Market Power	-0.117*	0.016	-0.789**	0.290
Liquidity	0.091**	0.126	0.083**	0.121
Momentum Return	0.051*	0.012	0.041**	0.023
Return on Equity	-0.061**	0.019	-0.097*	0.041
Price to Earnings ratio	-0.179**	0.108	-0.166**	0.134
Dividend Yield	-0.071*	0.051	-0.280*	0.054
R-squared	0.104		0.158	

Number of obs	8621		8620	
F-test	66.45		88.192	
Prob > F	0.000		0.000	
Hausman Chi-square test value	154.69		34.78	
P-value	0.000		0.000	
		China		
Variables	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**
Constant	0.062**	0.013	0.0321**	0.054
Firm Size	-0.013***	0.050	-0.015**	0.019
Leverage	0.050**	0.364	0.024*	0.013
Market Power	-0.068**	0.023	-0.0421**	0.068
Liquidity	0.053*	0.525	0.179**	0.204
Momentum Return	0.019**	0.096	0.0787**	0.051
Return on Equity	-0.012**	0.048	-0.018*	0.024
Price to Earnings ratio	-0.043**	0.033	-0.077**	0.016
Dividend Yield	-0.014**	0.025	-0.040**	0.012
R-squared	0.103		0.157	
Number of obs	113765		113764	
F-test	14.69		12.98	
Prob > F	0.000		0.001	
Hausman Chi-square test value	13.97		16.85	
P-value	0.000		0.000	
		South Africa		
Variables	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**
Constant	0.116***	0.574	0.060**	0.177
Firm Size	-0.061**	0.038	-0.026**	0.042
Leverage	0.702**	0.334	0.928*	0.378
Market Power	-0.324**	0.409	-0.223**	0.462
Liquidity	0.487***	0.455	0.403**	0.618
Momentum Return	0.658**	0.122	0.765**	0.138
Return on Equity	-0.531**	0.389	-0.164*	0.144
Price to Earnings ratio	-0.169*	0.487	-0.441**	0.551
Dividend Yield	-0.013*	0.231	-0.049**	0.926
R-squared	0.123		0.136	
Number of obs	2613		2612	
F-test	22.63		34.29	
Prob > F	0.030		0.000	
Hausman Chi-square test value	45.796		25.92	
P-value	0.001		0.000	

Note: The table represents the robustness results of panel data regression of all manufacturing firms. Model 1 shows the fixed effects results by estimating IR through one factor CAPM and Model 2 shows the fixed effect results by including the lag values of all independent variables. Their coefficients and standard errors are presented in the table. Hausman test is applied to select the fixed effect or random effects estimator. Hausman test Chi-square and p-value are also given in the table. *, **, and *** indicate the significance at the 1%, 5%, and 10% levels, respectively.