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THE SHARIAH-COMPLIANT RISK FACTOR AND DISTRESS RISK: EVIDENCE FROM THE U.S. STOCKS

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ABSTRACT

This paper tests the Shariah-compliant-augmented three-factor model (TFM) in the U.S. stock market from July 2005 to June 2024. In particular, we investigate whether the Shariah Compliant (SC) risk factor, measured as the difference in returns between the portfolio of non-Shariah-compliant (NSC) firms and that of SC firms, constitutes a systematic source of risk able to explain financial distress. We find that the SC risk factor is a major determining factor in pricing of stock portfolios classified by size, book-to-market and Shariah compliance, along with those of distressed and non-distressed firms. Additionally, we point out that the SC risk factor explains the cross-section of stock returns even when other financial distress risk factors are considered, suggesting that it contains significant distress-related information. Finally, we show that this risk factor is significantly related to innovations in term spread, which is consistent with Merton's ICAPM explanation. Overall, the findings indicate that the SC factor represents a systematic, undiversifiable distress risk factor. These results have important implications for asset management using SC stocks, supporting an SC-augmented TFM to fairly value assets and suggesting that SC investment may provide protection against financial distress.

Keywords: Islamic investment, Asset pricing, Financial distress, Systematic risk factors.
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I. INTRODUCTION

Multi-factor asset pricing models are founded on the concept that risk factors must be correlated with state variables that predict investment opportunities, a premise that justifies a risk premium. Confirmation of such a pattern offers a risk-based rationale for the factors in the context of Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM). Within this framework, Fama & French (FF) (1993) extend the capital asset pricing model (CAPM) by adding two risk factors designed to capture the size effect (SMB) and the value effect (HML). They consider these factors as premiums for state variables related to relative distress risk. Although, the empirical validity of the TFM (FF,1993), the literature on asset pricing continues to propose various alternative or additional variables to SMB and HML risk factors to better explain the variations of stock returns. Ferguson & Shockley (2003), for instance, show that leverage and relative distress portfolios factors serve as robust alternatives to FF risk factors. Boubaker et al. (2018) and Mselmi et al. (2019), support the role of the leverage variable as an additional default risk factor. Another stream of research explores the use of macroeconomic variables as substitutes for the HML and SMB factors (Leite et al., 2020).

In another line of research in finance, literature on Islamic investment has been gaining the interest of academics and practitioners in recent years. Unlike conventional investment, Islamic investment applies qualitative and quantitative screening methods to exclude stocks that do not adhere to Shariah guidelines and principles (Erragragui et al., 2016; Hassan et al., 2019). The qualitative screening excludes firms whose core business activities are inconsistent with Shariah law. According to DJIM index, examples include conventional financial services, tobacco, pork-related products, liquor, weapons, defence industries and entertainment activities. The quantitative screening removes companies with unacceptable levels of debt, accounts receivable and cash. A 33%[1] threshold relative to market capitalization or to total assets is commonly recognized by major indices such as Dow Jones and MSCI Barra.

According to Peillex et al. (2019), there are two opposing theoretical views regarding the effect of Shariah screening filter on return and risk. Within the modern portfolio theory framework (Markowitz, 1952), investors construct optimal portfolios that maximize returns while minimizing risk through asset diversification. According to this view, SC firms may incur higher risk compared to their NSC counterparts due to the screening process, which restricts the investment universe and consequently reduces diversification. In contrast, other arguments suggest that Islamic screening, particularly the debt ratio filter, may enable more efficient distress risk management, potentially offsetting the lower degree of diversification in SC portfolios. Although issuing debt allows firms to increase their value through tax deductibility, according to the trade-off theory the financial distress costs arise from increased debt financing. Indeed, firms with higher indebtedness tend to face greater default probability (Altman, 1968; Kraus & Litzenberger, 1973). In addition, agency costs resulting from divergences of interest between shareholders and debtholders may emerge when firms take on high levels of debt.

1 The AAOIFI sets a 30% threshold as specified in Shariah Standard No. 21.

Empirically, the exclusion of highly indebted companies from SC portfolios is often cited as a one of the most prominent arguments explaining their resilience during recessions (Akguc & Al Rahahleh, 2021). In this regard, Asutay et al. (2022) show that, during the global financial crisis, Islamic indices exhibit better performance in the US, European and Asia–Pacific markets. Brahmana & Kontesa (2024) report that a higher level of SC debt financing in firms' balance sheets makes them more resilient to stock price crashes. Uddin et al. (2017) conclude that Islamic banks are less vulnerable to credit risk since their activities tend to avoid interest-based financing. Nevertheless, some studies argue that SC principles do not consistently put the SC firms in a safe position. The constrained access to external funding sources for SC firms may restrict their financial flexibility and hinder their ability to meet financial obligations and operational needs (Alnori & Alqahtani, 2019). Moreover, it may force the SC firms to favor equity financing over debt financing, which inherently increases their investment equity risk (Akkizidis et al., 2008). According to Mohd Noor et al. (2018), Islamic institutions are exposed to the same risks faced by the conventional ones. However, they are also exposed to specific risks arising from the need to offer financial products and services that adhere strictly to Shariah guidelines. The unique contractual features of these products make it more challenging for SC financial institutions to mitigate risks (Adawiyah, 2015).

Although the literature on Islamic finance has become very popular, the link between Islamic investment and financial performance remains controversial. According to Trabelsi et al. (2020), Setiawan & Oktariza (2013), Lobe et al. (2012), Dharani & Natarajan (2011), Albaity & Ahmad (2008), Girard & Hassan (2008), the performance differences between SC investment and their conventional counterpart are insignificant. However, some studies (Derigs & Marzban, 2008; Al-Shakfa & Lypny, 2011; Hayat & Kareussl, 2011; Abu-Alkheil et al., 2018) find that restricting the investment universe to SC portfolios seriously harms diversification opportunities and leads to greater risk exposure. Conversely, other studies have demonstrated the superior performance of SC investment relative to the NSC one, especially during crisis periods (Cheong, 2021; Akguc & Al Rahahleh, 2021; Makni et al., 2015; Ashraf & Mohammad, 2014; BinMahfouz & Hassan, 2012; Alam & Rajjaque, 2010; Abdullah et al., 2007; Elfakhani et al., 2005). Touti & Taïb (2023) have proposed developing asset pricing models that consider the characteristics of Islamic finance to assess the fair value of SC assets. However, several studies in the Islamic finance literature use conventional asset-pricing models to examine the risk-return differences between Islamic and conventional firms. For instance, Sensoy (2016) and El Alaoui et al. (2016) use the CAPM to analyse an Islamic portfolio's sensitivity to market systematic risk. Dharani et al. (2019) and Ashraf (2016) utilize FF and Carhart multi-factor asset pricing models to investigate the performance of Shariah and conventional stocks. Safiullah & Shamsuddin (2021) and Halim (2023) test the sensitivity of SC portfolios to FF factors, as well as to profitability and investment risk factors, using the FF five-factor model. Unlike these earlier predecessors' studies, Merdad et al. (2015), Dharani et al. (2019), and Dharani et al. (2024) include an SC risk factor in the FF TFM. Empirical findings indicate that exposure to Islamic-related systematic risk is significantly priced in the Saudi Arabian, Indonesian and Indian markets. However, the specific nature of the risk reflected by this factor is not clarified by the authors.

As evidence that risk factors related to economic and financial fundamental risk are crucial for understanding asset pricing, we aim to bridge the gap of existing literature by offering a risk-based justification for the SC risk factor. Given the characteristics of Islamic investment, we expect that SC firms with lower leverage and lower account receivable cash exhibit lower financial distress risk as they are less exposed to cash flow volatility and credit market (Hussain et al., 2018). Consequently, the SC risk factor is expected to represent a risk premium related to relative financial distress for holding NSC over SC firms. Since several studies consider the SMB and HML variables as reliable indicators for financial distress, we employ an SC-augmented TFM to examine two hypotheses. First, we test whether the SC risk factor represents a systematic source of risk that is priced in the equity returns (H1). Second, we test whether the SC factor proxies for financial distress risk (H2).

Our study offers three key contributions to the existing literature. First, to our knowledge, this study represents the first work to combine three strands of literature: empirical asset pricing, corporate distress risk, and Islamic investment. Indeed, this paper advances the literature on the FF TFM by proposing the SC risk factor as an additional systematic financial distress risk. Contrary to Merdad et al. (2015) who used only the FF TFM, our analysis includes additional distress-related factors, beyond SMB and HML, to compare their explanatory power with the new factor. Moreover, we investigate whether the SC risk factor proxies for shocks in variables that describe investment opportunity t in the ICAPM framework. Second, no prior study has explored the SC risk factor using US data. If the SC risk factor is a relevant distress risk factor, the SC-augmented TFM will become the most appropriate pricing model in American context. Third, the findings can advance the Islamic finance industry by shedding light on the observed return differentials between SC and conventional stocks.

The paper is organized as follows. Section 2 reviews the theoretical framework and empirical studies. Section 3 details the data and research methodology. Section 4 reports and discusses the results, followed by a robustness analysis in Section 5. Section 6 provides the conclusion.

II. LITERATURE REVIEW

This section is split into two subsections: the first addresses Islamic finance and investing process, while the second extends previous studies on financial distress risk pricing models and the sensitivity of SC investment to financial distress.

2.1. Shariah-Compliant Investment

Islamic finance can be regarded as a distinct form of ethical finance that adheres to Shariah principles, derived from three primary sources: firstly, the Quran, the Holy Book of Islam; secondly, the Sunna, which encompasses the teachings and sayings of Prophet Muhammad (PBUH); and finally, Ijtihad, which involves deductions made by Muslim scholars regarding matters not explicitly addressed in the Quran and Sunna (Franzoni & Ait Allali, 2018).

To ensure Shariah compliance, the Islamic equity market operates under specific Islamic financial principles and guidelines, distinguishing it from conventional financial markets (Touti & Taïb, 2023). First, the prohibition of financial activities involving payment or reception of interest. Indeed, interest represents an increase in capital without assuming any risk related to investment or other productive activities (Iqbal & Mirakhor, 2011). In Islam, Money is regarded only as medium of exchange, not an asset that generates profit on its own (Marisya et al., 2024). As a result, banks, brokerage firms and other interest-based institutions, cannot be included in the Islamic equity market. Also, preferred stocks are not considered as SC financial instruments, as they guarantee fixed-income payments. As an alternative to interest-bearing financial transactions, Shariah promotes profit and loss sharing contracts between fund providers and users of funds. Secondly, excessive uncertainty in contracts and speculative behavior are banned in SC transactions. Moreover, Islamic firms are not allowed to engage in short-selling or invest in high-risk instruments such as toxic assets and derivative products, which have acted as a catalyst for the 2008 global financial crisis and exerted detrimental effects on conventional firms (Trichilli et al., 2020). Finally, the core activities of firms must not conflict with Islamic theological principles. Accordingly, businesses involved in non-medicinal alcohol, pork, tobacco, adult entertainment, and weapons or defense products are not permissible for investment, manufacturing or distribution.

As interest in Islamic equities grows among Muslim and non-Muslim investors (Asutay et al., 2022), several Islamic indices have been developed, providing screening systems to identify and select SC firms. Although the screening criteria differ across indices, SC investment are required to meet both qualitative and quantitative filter standards. The first step removes firms with unacceptable primary business activities, as discussed above, followed by financial ratio screening focused on debt and asset liquidity. For instance, DJIM index excludes companies whose total interest-bearing debt, account receivable and cash exceed 33% of their trailing 24-month average market capitalization. As mentioned by Merdad et al. (2015), the 33% threshold was introduced by Shariah scholars because firms find it challenging to strictly adhere to all Shariah rules, particularly in modern financial systems where interest-based practices are common.

2.2. Previous Studies

2.2.1. Previous Studies on Financial Distress Risk Pricing Models

Research on financial distress risk pricing models has been strongly influenced by the pioneer studies of FF (1993, 1996) who argue that firm size and the B/M ratio are good proxies for financial distress risk that should be remunerated. However, the financial distress premium is rather contentious and has continued to be the centerpiece of debate in the last two decades. While some authors claim that distress risk is due to idiosyncratic factors and support the CAPM (Campbell et al., 2011; Hanafi et al., 2021), others provide evidence argue that the two factors SMB and HML are insufficient to capture all distress risk. In the literature, several researchers consider that default risk and leverage factors can complement the size and B/M factors of FF (1993) in capturing financial distress.

Ferguson & Shockley (2003) propose to augment the CAPM model with two risk factors namely, firm leverage and financial distress risk. The results confirm their explanatory power in cross-sectional returns. According to Vassalou & Xing (2004), SMB, HML and the default risk factor together capture important variations in equity returns. Mselmi et al. (2019) highlight the superiority of the FF (1993) model augmented by financial distress risk in the French stock market. Khan & Iqbal (2021) conclude that adding a default risk factor to the five-factor model of FF (2015) enhances its ability to predict returns of companies listed in Pakistan market.

Based on the assumption that high leverage is the main indicator of firm bankruptcy likelihood, several studies have focused on whether the financial leverage serves as a financial distress factor. Bhatt & Sultan (2012) show that the leverage factor has a significant impact on the variations of expected returns during crisis period. Koseoglu (2014) confirms that the leverage-augmented TFM offers a robust explanation to the Istanbul's cross -sectional stock returns. Jain & Singla (2022) analyze the role of leverage and liquidity on stock returns in the Indian stock market. They find that leverage and liquidity-augmented five-factor model outperforms the CAPM and the TFM. Mirza et al. (2013) finds that leverage is priced in stock returns, and its incorporation in the TFM does not erode the ability SMB and HML to explain returns. Boubaker et al. (2018) test the power of the HML, SMB, momentum, relative distress risk and leverage factors in explaining default risk market. Results point out the relevance of the FF factors and leverage as distress risk factors in the French financial market.

2.2.2. Previous Studies on the Sensitivity of SC Investment to Financial Distress Risk

Current research in the literature is focused on evaluating the sensitivity of Islamic equity investments to financial distress from different standpoints.

SC investment and debt screening:

Many studies suggest that Islamic investment offers the opportunity to hedge financial distress risk because SC investment limits leverage (Ho & Mohd-Raff, 2019; Shear et al., 2020). El Alaoui et al. (2017) examine the effect of Islamic screening on systematic risk for 689 firms in seven European countries between 2008 to 2013. They show that SC stocks exhibit less volatility than NSC stocks, indicating that limiting debt beyond the 33% threshold can act as a buffer against vulnerability to shocks. By contrast, Alnori & Alqahtani (2019) argue that using debt ratio in Islamic screening tends to select underleveraged firms, which are more likely to face underinvestment issues. Using a sample of 600 companies from different countries, Satt et al. (2020) analyse the relationship between the firms SC level and the cost of debt. They report that companies with higher level of Shariah compliance face less favourable credit terms. The authors explain that these firms cannot benefit from the disciplinary mechanism of debt to mitigate managers' opportunistic behaviour. Brahmana & Kontesa (2024) analyse data from 344 Malaysian companies over the period 2012–2019 and conclude that a higher proportion of SC debt financing reduces stock price crashes. Bayram et al.

(2023) demonstrate that diversifying a portfolio with SC assets can be an effective strategy for risk averse-investors.

SC investment and Interest rate:

One area of research on Islamic investment explores how interest rate volatility affects the co-movement of stock market return. Rana & Akhter (2015) find a significant impact of interest rate on the conventional index (KSE-100), but not on the Islamic index (KMI-30). Shamsuddin (2014) confirms these findings, showing that DJIM indices exhibit lower exposure to interest rate risk than conventional indices. In contrast, Umar et al. (2018) find insignificant differences in sensitivity to interest rate between the DJIM index and its counterpart, concluding that Islamic stocks do not hedge against interest rate volatility.

SC investment and crisis periods:

According to Trichilli et al. (2020), the Islamic financial market remained resilient through the subprime crisis, while most major US and European investment companies collapsed. Trabelsi & Naifar (2017), Yahyaee et al. (2020), and Asutay et al. (2022) stated that during periods of market turbulence, investors were able to manage the risk associated with their portfolios by investing in Islamic funds. Mwamba et al. (2017) confirm that SC investments were less volatile than the conventional ones during the Black Swan and Asian currency crises. Ashraf (2022) shows that Islamic quantitative screening helped SC firms in Pakistian market become more resilient in responding to the Covid-19 health crisis. Hassan et al. (2022) confirm this finding in Asian markets. However, they show that during this period, Islamic as well as conventional stock indices exhibited increased volatility and a drop in valuations across regions such as America, Europe and the Middle East & Africa. Using a sample of 2160 firms across six geographic regions, Cheong (2021) finds that SC stocks are more resilient in Muslim-majority countries. He attributes the better performance of SC firms' equities to religious norms influencing investors, who prefer stocks aligned with their moral beliefs.

SC investment and asset pricing factors:

Much of the research on Islamic investment performance uses the CAPM model and reports mixed results. Ashraf (2016) finds that risk-adjusted returns do not differ between Islamic equity indices and conventional ones during the period 2000-2012. However, Ashraf & Khawaja (2016) reach the opposite conclusion, suggesting that SC portfolios were less risky than their conventional benchmark indices in the USA, Canada, Europe, the GCC, and Japan between 2003 and 2013. El Alaoui et al. (2017) examine systematic risk across seven European countries and show that, overall, SC portfolios tend to exhibit lower systematic risk compared to NSC portfolios.

Other studies employ multifactor pricing models to evaluate the returns of SC stocks. Bhatt & Sultan (2012) use the TFM augmented by the leverage risk factor to examine the performance of 3704 stocks between 2000 and 2009. Their findings indicate SC stocks experience lower sensitivity to leverage risk factor compared to conventional stocks, suggesting that they can be more suitable for wealth preservation. Using the four-factor model of Carhart (1997), Lobe & Walkshäusl

(2012) observed that Islamic indices tend to favor growth and momentum stocks. Their analysis was based on MSCI Index data spanning 2002 to 2011. Nainggolan et al. (2016) employ the same asset pricing model to analyse 387 equity funds domiciled in 32 countries over the period 1984-2010. They demonstrate that Islamic funds were more risky than conventional funds. Safiullah & Shamsuddin (2021) show that Islamic portfolios have better performance and lower cost of capital than their conventional counterparts, using the five-factor model of FF (2015). However, Halim (2023) find that the SC portfolios are more sensitive to the market portfolio, indicating a lack of diversification within these portfolios.

From the foregoing review, two broad conclusions can be drawn. First, studies on default risk pricing models generally support an augmented FF TFM. Second, no work has established a direct relationship between SC investment and distress risk. Third, studies comparing the risk-adjusted returns of SC and NSC investments are based on conventional asset pricing models, which can be inappropriate for accurately assessing SC stock returns. To address this gap, this paper aims to explain the nature of return differential between SC and NSC investments from the perspective of systematic financial distress risk. Merdad et al. (2015) propose a study in this direction by augmented the TFM of (FF, 1993) by a SC risk factor calculated as the excess return of NSC firms compared to SC firms. The results clearly reflect that the SC risk factor is priced in Saudia Arabian financial market, but the nature of risk it captures remain a puzzle. Based of the preceding discussions, we propose the following hypothesis.

H1: The SC risk factor represents a systematic risk factor that affects the cross-sectional expected returns.

H2: The SC risk factor captures financial distress risk.

III. METHODOLOGY

3.1. Data

Our sample encompasses stocks listed in the S&P500 index. The selection of U.S. market is motivated by several factors. The U.S. is a developed economy and home to some of the oldest and most reliable Islamic index providers (Anwer et al., 2020) such as the Dow Jones Islamic Market World Index. Notably, the Dow Jones Indices collaborate with Ratings Intelligence Partners, a consultancy institution with qualified and prominent Shariah scholars, who develop the screening methodology and provide guidance to ensure Shariah compliance. Additionally, with 71.8% of total market capitalization, the U.S. stock market holds the largest weight in the DJIM. Moreover, the scarcity of studies assessing the SC risk factor in this market[2] can offer useful findings and new insights (Balli et al., 2022). Although, Halim (2023) argue that analysing the performance of SC firms in non-Muslim countries may produce biased results due to their skewed investment behaviour toward certain firm-specific characteristics (size, growth, liquidity, profitability, etc), others hold a different point of view. They suggest that SC firms should be evaluated objectively, free from the influence of socio-cultural norms (Cheong, 2021; Shear et al., 2020).

2 Merdad et al. (2015), Dharani et al. (2019), Dharani et al. (2024) estimate the Islamic effect factor in different regions, namely the Saudi Arbian, Indian and Indonesian Markets.

Financial and banking firms are not considered, given their different capital structure and risk characteristics. Firms with missing data or a negative B/M ratio are excluded in a given year but reintegrated once the required data becomes available. Thus, the annual number of stocks varies and contains up to 400 companies. Table 1 presents the sectoral composition of the firms included in the sample. The Consumer Services sector has the highest number of equities (76), followed by the Industrials sector (68). The Basic Materials sector has the lowest representation (15).

Table 1.
Sectoral Classifications

Sector	Number of Equities
Basic Materials	15
Telecommunications	20
Utilities	25
Consumer Goods	39
Oil & Gas	47
Health Care	52
Technology	58
Industrials	68
Consumer Services	76
Total	400

This table presents the classification of firms listed in the S&P 500, excluding the financial sector. The firms are grouped according to their primary industry sector.

To collect the data required in this study, we use different databases: monthly stock prices and annual financial and accounting data are acquired from Thomson-Reuters Datastream, the SC firms used are taken from the DJIM's constituent annual lists provided by the S&P Dow Jones support team. The corresponding data are used to create portfolios based on the market capitalisation, as a size measure; the B/M ratio; Shariah compliance; the total debt to total asset as a leverage measure, and Altman's Z-score which is calculated as follows:

$$\text{Z-score} = 1.2(NWC/TA) + 1.4(RE/TA) + 3.3(EBIT/TA) + 0.6(ME/TD) + 1.0(R/TA) \quad (1)$$

with NWC is net working capital (Current Assets – Current Liabilities); TA is total assets, RE is retained results, ME is market equity; TD is total debt; EBIT is results before interest and taxes and R is total revenue.

The study requires collecting a number of macroeconomic data extracted from database of the Federal Reserve Bank of St. Louis. The macroeconomic variables include: the term spread (TERM: measured as the difference between the 10-year and the 1-year Treasury yields), the dividend yield (DIV) of the value-weighted S&P500 portfolio, the default spread (DEF: measured as the difference between Baa corporate bonds yield and the yield on the 10-year Treasury), the inflation rate

(INF calculated based on changes in the Consumer Price Index) and the 1-month Treasury bill yield (ST).

We consider the period from July 2005[3] to June 2024, i.e. 228 months to calculate monthly returns. However, data used to construct portfolios are collected at fiscal year-ends to ensure they are known before the returns they are supposed to explain (FF, 1992). The literature highlights that long monthly data series covering different crisis periods are essential for studying equity pricing (Boubaker et al.,2018). Accordingly, our study sample includes major crises such as the subprime crisis (2007–2009) and the COVID-19 pandemic (2020–2021), allowing for a relevant analysis of the robustness of financial distress risk factors (Cochrane, 2001).

3.2. Method

In this study, we examine whether the SC risk factor represents a systematic risk (hypothesis H1) and whether it proxies for distress risk (hypothesis H2). We test these hypotheses by including the SC risk factor in the TFM (FF, 1992; 1993). Recently, the five-factor model (FF, 2015) has been commonly used as a benchmark to describe the cross-section of average returns. However, for comparison purposes, we adopt the methodology of Merdad et al. (2015). Further, the discussion in the literature regarding whether the new factors in five-factor model are related to distress risk remains sparse and inconclusive (Leite et al., 2020; Khan & Iqbal, 2021; Singh & Chakraborty, 2025).

Three commonly used methodologies in the literature for evaluating asset pricing model performance are applied within regression analysis (FF, 2020; Lettau & Pelger, 2020; FF, 2015; Wang, 2013; Menzly et al., 2004; FF, 1993; Fama & MacBeth, 1973). The first is a portfolio-based time-series regression approach. The second applies the cross-section regressions by using the GMM methodology to individual stock returns. As noted by FF (2020), individual stocks can be used in cross-sectional regressions; however, small stocks often exhibit extreme characteristics and returns, which may bias the results in time-series regressions. Using portfolio stock returns instead downweighs small stocks and alleviates this issue. Since economic-related risks are crucial for the reliability of risk factors, the third test examines the relation between the SC risk factor and innovations in macroeconomic variables (Petkova, 2006; Leite et al., 2020). Each of the three methodologies is described in the subsequent sections.

3.3. Proposed Model and Econometric Approach

3.3.1. Time-series Regression Approach of Portfolio Returns

In our initial asset-pricing tests, we examine if the SC risk factor is priced using time-series regressions. Following FF-style portfolio approach, we analyse 12 size, B/M and Shariah compliance portfolios. The second objective is to investigate whether the SC risk factor captures financial distress. To this end, we create two portfolios composed of distressed and non-distressed firms.

3 The starting year 2005 was determined by the data made available by the Dow Jones support team.

We test the SC-augmented TFM through the time-series regression below.

$$R_{pt} - RF_t = \alpha_p + \beta_p^M (RM_t - RF_t) + \beta_p^S SMB_t + \beta_p^H HML_t + \beta_p^{NS} NSMSC_t + \varepsilon_{pt} \quad (2)$$

With R_{pt} - RF_t is the return in excess of the risk-free rate (measured by the one-month Treasury bill yield) of the portfolio p for month t; α_p is the regression intercept of the model; β_p^M, β_p^S, β_p^H and β_p^{NS} are the coefficients of the following risk factors: the excess return on the market portfolio (RM_t-RF_t), the firm's size factor SMB_t, the B/M factor HML_t, and the SC risk factor $NSMSC_t$, and ε_{pt} is the error term.

We create equally weighted portfolios based on the intersection of portfolios sorted, independently, based on firm's size, B/M and shariah compliance. The June median market capitalization of year t is used to divide stocks into Small (S) and Big (B) portfolios for the period from July of year t to June of year t+1. Then, the December B/M of year t-1 breakpoints are defined as the top 30% (High, H), the middle 40% (medium, M), and the bottom 30% (Low, L) of the ranked B/M values of the stocks for the period from July of year t to June of year t+1. Finally, Stocks are classified into two SC and NSC (NS) firms for the period from July of year t to June of the year t+1 formed based on the DJIM US constituent list of year t-1. In total, we have 2x3x2= 12 portfolios (SHNS, SHSC, SMNS, SMSC, SLNS, SLSC, BHNS, BHSC, BMNS, BMSC, BLNS and BLSC). The average of the monthly returns on these portfolios are the explanatory variables, calculated as shown in Table 2.

Table 3 provides descriptive statistics of the NSMSC factor, the market portfolio and the two FF factors. The premiums associated with market and SMB risk factors are positive, while those for HML and NSMSC portfolios are negative. The highest premium volatility is observed for market and HML portfolios. Arbitrage strategy based on size appears to be the most efficient. Additionally, the NSMSC portfolio return has a negative correlation with the market portfolio and HML.

For the dependent variables, we consider the 12 previously defined portfolios. Additionally, we construct two portfolios based on Altman (1968)'s Z-score, calculated from the prior year-end accounting data, to annual portfolios for each subsequent year. Firms with a z-score > 2.99 form the non-distressed portfolio (HZ), while firms with a z-score ≤2.99 form the distressed portfolio (LZ).

Table 4 summarizes the excess returns of the dependent variables, showing that the 12 stock portfolios have average monthly excess returns ranging from 0.43% to 1.23%. In every B/M class, the average returns decrease with the size for both SC and NSC portfolios. Moreover, small-firm portfolios exhibit higher risk than big-firm portfolios, supporting risk-return trade-off and market efficiency. For big firms, portfolios with high B/M ratios have lower returns than those with low B/M ratios, while the opposite holds for small firms. Unlike Merdad et al. (2015), the negative SC effect on stock returns is observed only in the medium-B/M group. Table 4 also shows that LZ portfolio earns higher returns and carries less risk than HZ portfolio.

Table 2.
Summary of Risk Factor Definitions

Factor Name	Definition	Construction
$RM - RF$	Market factor	RM=(SHNS+SHSC+SMNS+SMSC+ SLNS+SLSC+ BHNS+BHSC+BMNS+BMSC+BLNS+ BLSC)/12 RF= Return on one-month Treasury bill rate.
SMB	The size factor: defined as the return differential between the portfolio of small and big capitalisations.	SMB=(SHNS+SHSC+SMNS+SMSC+SLNS+SLSC)/6-(BHNS + BHSC+BMNS+BMSC+BLNS+BLSC)/6
HML	The value factor: defined as the return differential between portfolios of firms with high B/M and low B/M.	HML=SHNS+SHSC+BHNS+BHSC)/4-(SLNS+ SLSC+BLNS+BLSC)/4
$NSMSC$	SC risk factor: defined as the return differential between portfolios of NSC firms and SC firms.	NSMSC=SHNS+SMNS+SLNS+BHNS+BMNS+BLNS)/6-(SHSC+SMSC+SLSC+BHSC+BMSC+BLSC)/6
LEV	Leverage risk factor: defined as the return differential between portfolios of firms with high leverage and low leverage.	LEV= SHHD+SMHD+SLHD+BHHD+BMHD+BLHD)/6-(SHLD+SMLD+SLLD+BHLD+BMLD+BLLD)/6
DEFZ	Default risk factor: defined as the return differential between portfolios of distressed firms and non-distressed firms.	DEFZ=SHLZ+SMLZ+SLLZ+BHLZ+BMLZ+BLLZ)/6-(SHHZ+SMHZ+SLHZ+BHHZ+BMHZ+BLHZ)/6

Table 3.
Descriptive Statistics for Risk Factors in the Time-Series Regressions

	Monthly returns			
	RM-RF	**SMB**	**HML**	**NSMSC**
Mean (%)	1.06	0.44	-0.28	-0.03
Standard deviation (%)	5.12	1.80	2.79	2.20
	Correlation			
	RM-RF	**SMB**	**HML**	**NSMSC**
RM-RF	1			
SMB	0.457***	1		
HML	0.249***	0.342***	1	
NSMSC	-0.107***	0.060***	-0.197***	1

Note: RM-RF is the market factor, SMB is the size factor, HML is the value factor and NSMSC is the SC risk factor. Sample period: July 2005 to June 2024 (228 monthly returns).

Table 4.
Descriptive Statistics for Dependent Variables in the Time-Series Regressions

		NSC			SC		
		Book-to-market					
		H	**M**	**L**	**H**	**M**	**L**
		Mean (%)					
Size	S	0.92	1.04	1.23	1.11	0.94	1.29
	B	0.43	0.55	1.03	0.60	0.53	0.67
		Standard deviation (%)					
Size	S	6.29	5.32	6.00	6.86	5.76	5.29
	B	4.83	4.58	5.87	6.19	4.63	4.69
		HZ				**LZ**	
		Mean (%)					
		0.93				1.22	
		Standard deviation (%)					
		4.87				8.97	

3.2.2. Cross-sectional Regression Approach for Individual Stock Returns

The GMM method is used to examine the ability of the NSMSC factor in explaining the cross- sectional returns of individual stocks. Moreover, following several studies (Vassalou, 2003; Boubaker et al.,2018; Mselmi et al., 2019), we include, in addition to the SMB and HML, the leverage (LEV) and financial distress risk (DEFZ) factors, which have been shown to successfully capture the default risk. If the NSMSC factor proxies for financial distress risk, SMB, HML, LEV, and DEFZ should lose explanatory power once it is included.

In our cross-sectional regressions, we consider individual stocks as dependent variables instead of portfolios. To test whether our measure captures default risk, we separate SC firms from NSC ones as described in Figure 1. Significant differences in loadings on the distress risk factors would suggest that default risk plays an important role in pricing these equities.

We examen six alternative model specifications:

Model 1 $r_i - r_f = \lambda_0 + \lambda_M (r_M - r_f) + \lambda_S SMB + \lambda_H HML + \varepsilon_i$ (3)

Model 2 $r_i - r_f = \lambda_0 + \lambda_M (r_M - r_f) + \lambda_S SMB + \lambda_H HML + \lambda_{NS} NSMSC + \varepsilon_i$ (4)

Model 3 $r_i - r_f = \lambda_0 + \lambda_M (r_M - r_f) + \lambda_S SMB + \lambda_H HML + \lambda_D DEFZ + \varepsilon_i$ (5)

Model 4 $r_i - r_f = \lambda_0 + \lambda_M (r_M - r_f) + \lambda_S SMB + \lambda_H HML + \lambda_D DEFZ + \lambda_{NS} NSMSC + \varepsilon_i$ (6)

Model 5 $r_i - r_f = \lambda_0 + \lambda_M (r_M - r_f) + \lambda_S SMB + \lambda_H HML + \lambda_L LEV + \varepsilon_i$ (7)

Model 6 $r_i - r_f = \lambda_0 + \lambda_M \left(r_M - r_f\right) + \lambda_S SMB + \lambda_H HML + \lambda_L LEV + \lambda_{NS} NSMSC + \varepsilon_i$ (8)

with r_i-r_f is the monthly excess returns on stock ***i*;**. λ_0 is the regression intercept**;** λ_M, λ_S, λ_H, λ_C, λ_D and λ_L are the risk premiums related to: market (r_M-r_f), size (*SMB*), B/M (*HML*), SC effect (*NSMSC*), leverage (*LEV*) and relative distress risk (*DEFZ*), respectively and ε_i is the error term.

We follow the same FF-style portfolio approach to define leverage/financial distress portfolios (see, Table 2). Table 5 provides summary statistics for the returns of the six risk factors. Similar to HML and NSMSC, the average returns of the DEFZ and LEV portfolios are negative. We also find that NSMSC is positively correlated with LEV and DEFZ.

The empirical investigation is performed by regressing the monthly returns of SC and NSC stocks on the specified risk factors. SC firms are those listed in S&P500 index that remain compliant with Islamic screening throughout the entire period, while NSC stocks are those that are listed in S&P500 and have never appeared in the DJIMI list. The final dataset includes 84 SC stocks and 94 NSC stocks.

Table 6 presents the summary statistics for SC and NSC firms. SC stocks show a higher average return than their NSC counterparts and display lower standard deviation. The skewness and kurtosis statistics suggest that the prices of both SC and NSC stocks do not follow a normal distribution, with NSC stocks showing a more pronounced peak. These results indicate that SC investment provided more stable returns than NSC one.

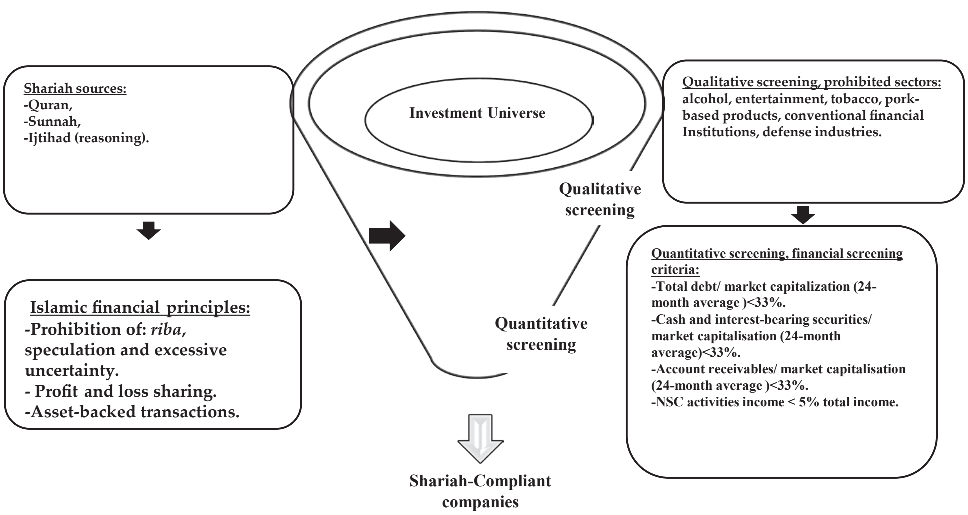

Figure 1.
SC Screening Using DJIM Method

Table 5.
Descriptive Statistics for Risk Factors in the Cross-Sectional Regressions

	r_M-r_f	SMB	HML	NSMSC	DEFZ	LEV
Mean (%)	1.06	0.44	-0.28	-0.03	-0.05	-0.18
St. deviation (%)	5.12	1.80	2.79	2.20	2.28	1.84
			Correlation			
r_M-r_f	1					
SMB	0.457***	1				
HML	0.249***	0.342***	1			
NSMSC	-0.107***	0.060***	-0.197***	1		
DEFZ	0.276***	0.314***	0.447***	0.230***	1	
LEV	-0.305***	-0.158***	-0.075***	0.388***	0.166***	1

***, **, and *: statistical significance levels at the 1%, 5%, and 10%, respectively.

Note: RM-RF is the market factor, SMB is the size factor, HML is the value factor and NSMSC is the SC risk factor, DEF is the default risk factor and LEV is leverage risk factor. Sample period: July 2005 to June 2024 (228 monthly returns).

Table 6.
Descriptive Statistics for SC and NSC Stocks in the Cross-sectional Regressions

	SC Stocks	NSC Stocks
Mean	0.090	0.007
St. deviation	0.081	0.093
skewness	-0.11	0.78
kurtosis	6.81	18.81

3.2.3. The Relationship between the SC Risk Factor and Macroeconomic Indicators

We investigate the relationship between the NSMSC factor, the FF factors and innovations in state variables, namely the term spread, the dividend yield, the default spread, the inflation rate and the yield on the 1-month T-bill. The hypothesis that the SC risk factor is a measure of distress risk can be tested by examining whether it is significantly related to the default spread.

Following Campbell (1996), we estimate the innovations of the set of macroeconomic variables by using a first-order VAR with nine variables. The model is written in a matrix form as follows:

$$Z_t = A_0 + A_1 Z_{t-1} + \varepsilon_t \tag{9}$$

With Z_t is the vector that contains RM, SMB , HML, NSMSC, TERM, DIV, DEF, INF and the ST; A_0 is the (9 x 1) vector of constants; A_1 is the (9 x 9) matrix of coefficients and ε_t is the vector of variable innovations denoted ε_t^{RM}, ε_t^{SMB}, ε_t^{HML}, ε_t^{NSMSC}, ε_t^{TERM}, ε_t^{DIV}, ε_t^{DEF}, ε_t^{INF}, and ε_t^{ST}.

The VAR system in equation (8) is triangularized by keeping the excess market return innovation unchanged, orthogonalizing the innovation in TERM ($\hat{\varepsilon}_t^{ITERM}$) to the excess market return, and similarly for the other innovations. All innovations are scaled to match the market factor's variance. We run the following time series regressions:

$$\hat{\varepsilon}_t^I = c_0 + c_1(RM_t - RF_t) + c_2 SMB_t + c_3 HML_t + c_4 NSMSC_t + u_t \tag{10}$$

With I ∈ {TERM, DIV, DEF, INF, ST}, c_0 is the regression intercept of the model; c_1, c_2, c_3 and c_4 are the regression coefficients of the excess market return portfolio (RM_t-RF_t), the size factor SMB_t, the value factor HML_t, the SC risk factor $NSMSC_t$, respectively. u_t is the error term.

From Table 7, we observe that the NSMSC factor is significantly related to term spread, the 1-month T-bill and the inflation rate. The correlation coefficient between NSMSC and the inflation rate is 0.133, which is the highest among the correlations between the NSMSC and the other macroeconomic variables.

Table 7.
Descriptive Statistics for FF Risk Factors, the SC Risk Factor, and Macroeconomic Innovation Variables

	Correlation								
	R_M	**SMB**	**HML**	**NSMSC**	**ε^{TERM}**	**ε^{DIV}**	**$\hat{\varepsilon}^{DEF}$**	**ε^{INF}**	**$\hat{\varepsilon}^{ST}$**
ε^{TERM}	0.026	0.171***	0.159**	-0.122*	1				
ε^{DIV}	-0101.	0.089	-0.002	-0.041	-0.028	1			
ε^{DEF}	-0.089	0.082	0.004	-0.033	0.555***	-0.877***	1		
ε^{INF}	-0.034	-0.221***	-0.148**	0.133**	-0.498***	-0.513***	---- 0.336***	1	
ε^{ST}	-0.016	-0.049	-0.114*	0.125*	-0.801***	-0.351***	-0.533***	-0.453	1

***, **, and *: statistical significance levels at the 1%, 5%, and 10%, respectively.

IV. EMPIRICAL RESULTS

4.1. Time-Series Regression Results

We estimate time-series regressions of monthly excess returns of our 12 stock portfolios on the market, HML, SMB and NSMSC factors. The corresponding time-series regression tests are reported in Appendix A. We use the TFM of FF (1993) as a benchmark. The results of the two empirical specifications covering the period from July 2005 to June 2024 are presented in Table 8.

The intercept in time-series regressions is commonly used to evaluate the performance of asset pricing models (Mselmi et al., 2019). According to FF (1993), the intercept should be close to zero. Our results show that, in the TFM, one regression exhibits an intercept that exceeds two standard errors from zero, compared with two intercepts in the SC-augmented TFM. Based on the adjusted-R^2 criterion, the SC-augmented TFM outperforms the TFM in explaining the common stock return variations, with an average adjusted- R^2 of 84.4% for the 12 portfolios, compared with 80.6%. This result is consistent with Merdad et al. (2015), who report an average adjusted-R^2 of 83% with the TFM augmented by SC risk factor.

Table 8.
Time-Series Regression Results of Twelve Sorted Portfolios

	TFM						SC-augmented TFM						
	α	β_M	β_S	β_H	Adj-R^2	F-stat	A	β_M	β_S	β_H	β_{NS}	Adj-R^2	F-stat
SHNS	-0.001 (-1.31)	0.886 (9.46)***	0.608 (3.36)***	0.431 (5.13)***	0.875	534.21***	-0.001 (-1.02)	0.914 (10.35)***	0.622 (5.06)***	0.544 (10.35)***	0.769 (9.08)***	0.914	600.91***
SHSC	0.001 (0.45)	0.958 (10.30)***	0.277 (1.44)	0.507 (4.36)***	0.784	276.69***	-0.001 (-0.70)	0.904 (10.52)***	0.619 (4.29)***	0.559 (5.88)***	-0.514 (-3.32)***	0.846	312.25***
SMNS	-0.000 (0.68)	0.848 (10.57)***	0.489 (3.05)***	-0.137 (-2.13)***	0.847	421.51***	-0.000 (-0.32)	0.850 (10.99)***	0.495 (3.53)**	-0.031 (-0.65)	0.276 (2.98)***	0.855	333.78***
SMSC	-0.003 (-2.80)***	0.934 (9.39)***	0.417 (2.93)***	-0.067 (-0.71)***	0.866	491.13***	-0.003 (-2.66)**	0.924 (9.72)***	0.650 (4.25)***	-0.157 (-2.67)***	-0.395 (-5.02)***	0.880	416.34***
SLNS	-0.001 (-1.01)	0.905 (9.12)***	0.755 (4.59)***	-0.486 (-4.55)***	0.764	246.19***	-0.002 (-1.72)*	0.889 (9.59)***	0.904 (6.11)***	-0.510 (-6.40)***	0.454 (3.74)***	0.822	261.56***
SLSC	0.001 (0.81)	0.911 (10.04)***	0.364 (2.91)***	-0.464 (-7.71)***	0.853	442.34***	0.001 (0.89)	0.864 (10.29)***	0.378 (2.89)***	-0.478 (-10.16)***	-0.583 (-8.06)***	0.870	380.42***
BHNS	0.000 (0.54)	0.823 (9.95)***	-0.482 (-3.92)***	0.340 (6.10)***	0.825	359.56***	-0.000 (-1.40)	0.833 (10.32)***	-0.360 (-2.95)***	0.385 (7.85)***	0.536 (7.36)***	0.843	303.46***
BHSC	-0.000 (-0.19)	0.993 (9.70)***	-0.493 (-2.77)***	0.491 (6.19)***	0.782	272.55***	0.000 (0.08)	0.992 (9.91)***	-0.567 (-3.22)***	0.523 (7.31)***	-0.580 (-5.12)***	0.841	299.33***
BMNS	-0.001 (-0.81)	0.815 (9.46)***	-0.307 (-2.58)***	-0.023 (-0.40)	0.792	289.21***	-0.000 (-0.63)	0.824 (9.83)***	-0.417 (-3.43)***	0.081 (1.39)	0.254 (2.64)***	0.803	230.70***
BMSC	-0.001 (-1.18)	0.862 (10.56)***	-0.410 (-3.62)***	-0.023 (-0.50)	0.841	403.43***	-0.001 (-183)	0.805 (10.76)***	-0.212 (-2.03)*	-0.066 (-1.77)*	-0.544 (-6.6)***	0.864	359.61***
BLNS	0.001 (0.44)	0.901 (9.51)***	-0.093 (-0.68)	-0.394 (-3.04)***	0.578	104.83***	0.001 (0.75)	1.035 (9.83)***	-0.736 (-2.89)***	-0.543 (-5.46)***	0.715 (4.14)***	0.737	159.29***
BLSC	-0.001 (-1.24)	0.919 (9.00)***	-0.385 (-3.41)***	-0.421 (-6.69)***	0.876	438.97***	-0.002 (-1.73)	0.855 (10.48)***	-0.234 (-1.81)*	-0.454 (-11.18)***	-0.375 (-6.00)***	0.861	349.50***

***, **, and *: statistical significance levels at the 1%, 5%, and 10%, respectively.

Note: This table reports the results from the TFM and the SC-augmented TFM. Dependent variables: 12 excess return portfolios created by size (small and big), B/M (low and high), and SC status (SC and NSC). Independent variables: RM–RF, SMB, HML and NSMSC. Sample period: July 2005 to June 2024 (228 monthly returns). Slopes (t-statistics in parentheses), adjusted R^2, and F-test are presented for each portfolio; standard errors corrected for heteroskedasticity using Newey-West (1980).

The results from the TFM indicate a strong positive correlation between the market risk factor and stock returns, with all β^M coefficients more than 9 standard errors from zero. In every B/M class, SMB slopes decline from small to big capitalization for both SC and NSC portfolios, confirming the negative relationship between size and average returns. Most of these coefficients are significant at 95%. Across all size quintiles and for both SC and NSC portfolios, HML slopes increase from negative to positive values, suggesting that there is a positive link between average returns and B/M ratio. Except for the SMSC, BMNS and BMSC portfolios, all coefficients are significant at 99%.

Table 8 also shows, that adding NSMSC factor to the FF model does not affect the relationship between the market factor, size and B/M and stock returns. We find loadings on NSMSC for all non-Islamic portfolios, SHNS (0.769), SMNS (0.279), SLNS (0.454), BHNS (0.536), BMNS (0.254) and BLNS (0.715), positive and significant at the 1% level. While the loadings on NSMSC for all SC portfolios, SHSC (-0.514), SMSC (-0.395), SLSC (-0.583), BHSC (-0.580), BMSC (-0.544) and BLSC (-0.375), are negative and significant at the 1% level. Our findings align with Merdad et al. (2015), who report that NSC firms earn higher returns than SC firms. Accordingly, the hypothesis (H_1) that the SC risk factor proxies for systematic risk is supported.

In the second stage, we test the TFM and the SC-augmented TFM for LZ and HZ portfolios. Table 9 shows that the loading on NSMSC factor is positive for LZ (0.574) and negative for HZ (-0.238). All these coefficient estimates are statistically significant at the 1% level. In both models, the coefficients on the SMB factor are insignificant, while HML coefficients are significant and negative (positive) for the portfolios of non-distressed (distressed) firms only in the SC-augmented TFM. These results provide evidence that the SC risk factor better captures distress risk compared with SMB and HML factors, supporting our second hypothesis (H_2).

Table 9.
Time-Series Regression Results of Distressed (LZ) and non-Distressed Portfolios (HZ)

	TFM						SC-augmented TFM						
	α	β_M	β_S	β_H	Adj-R^2	F-stat	α	β_M	β_S	β_H	β_{SC}	Adj-R^2	F-stat
LZ	0.001 (0.51)	1.369 (3.78)***	-0.410 (-0.97)	0.244 (1.63)	0.642	136.86***	0.000 (0.42)	1.390 (3.99)***	-0.411 (-0.99)	0.331 (3.60)	0.574 (3.81)***	0.649	105.45***
HZ	-0.000 (-0.13)	0.898 (10.29)***	0.011 (0.11)	-0.164 (-3.82)***	0.918	849.43***	-0.000 (-0.21)	0.874 (10.66)***	0.048 (0.49)	-0.172 (-5.68)***	-0.238 (-4.81)***	0.920	650.83***

***, **, and *: statistical significance levels at the 1%, 5%, and 10%, respectively

Note: This table reports the results from the TFM and the SC-augmented TFM. Dependent variables: 2 excess returns portfolios of non-distressed (HZ) and distressed (LZ) firms. Independent variables: RM–RF, SM B, HML and NSMSC. Sample period: July 2005 to June 2024 (228 monthly returns). Slopes (t-statistics in parentheses), adjusted R^2, and F-test are presented for each portfolio; standard errors corrected for heteroskedasticity using Newey-West (1980).

4.2. Cross-Sectional Regression Results

The cross-sectional regressions are estimated using the GMM methodology with an asymptotically efficient weighting matrix. For each model, the J-statistic is employed to test the over-identifying restrictions. The corresponding results are presented in Table 10.

For all the specifications examined, the market factor risk premium is highly statistically significant, with a*t*-statistic greater than 56.60. In contrast, we find that the size and value factors have an insignificant effect on the returns of both types of firms (the associated coefficients are statistically insignificant or have low values), regardless of the model considered. This finding is expected for the SMB variable given that the sample is restricted to large market capitalization firms in the U.S. equity market. Table 10, also, indicates that leverage (LEV) and relative distress (DEFZ) capture a large portion variation in stock returns for SC and NSC firms. On the other hand, the LEV/DEFZ factor loading is significantly negative for SC stocks and significantly positive for NSC stocks at the 1% level. These findings thus advocate that SC firms are less exposed to financial distress risk than NSC firms. In the SC-augmented TFM, the NSMSC's coefficient value is 0.218 for SC firms, which is statistically significant (z-statistic of 7.83), and 0.707 for NSC firms, also statistically significant (z-statistic of 22.93). This indicates that the SC risk factor incorporate a systematic component which is priced in the cross-sectional equity returns. The same results are observed even when the NSMSC factor is considered as part of the augmented models (see models 2, 4 and 6). Our first hypothesis (H1) is therefore supported.

Besides, in all models, the risk premium related to SC risk factor tends to be higher for NSC firms. This suggests that investors require a higher risk premium for bearing the growing distress risk of the NSC firms. Moreover, for these firms and in the presence of SC factor (see model 4 and 6) the LEV and DEFZ factors remain significant, but their loadings vary from 0.452 to 0.135 and from 0.357 to 0.130, respectively. Interestingly, we can infer from our results that the SC risk factor shares some common information related to distress risk with LEV and DEFZ, supporting our second hypothesis (H2). In the case for SC firms, it seems that LEV/DEFZ requires the presence of the SC risk factor for its coefficient to become larger and more significant.

Notice also that the fact that neither LEV nor DEFZ lose their explanatory power in the presence of NSMSC factor indicates that, there is additional information in these factors relevant for asset pricing. This evidence is similar to those of Vassalou & Xing (2004) and Mirza et al. (2013) about the relationship between SMB and HML and default risk.

Regarding the p-values for the J-test, they are higher than 0.1 in the case of SC firms, indicating that the null hypothesis of correct specification for all models cannot be rejected. This is further supported by the fact that the intercepts (λ_0) are not statistically significant. For NSC firms, however, the p-values of models 1 and 3 are significant, and the intercept (λ_0) is different from zero in model 3.

Table 10.
Cross-Sectional Regression Results of SC and NSC Firms
Panel A : SC Stocks

λ_0	λ_M	λ_S	λ_H	λ_L	λ_D	λ_{NS}	
			Model 1				**J-test**
0.000	0.821	0.040	-0.128				1.24
(1.12)	(65.21)***	(1.10)	(-5.71)***				(0.26)
			Model 2				
0.000	0.808	0.044	0.000			0.218	0.15
(0.39)	(6623)***	(1.22)	(-4.53)***			(7.83)***	(0.69)
			Model 3				
0.000	0.811	0.202	-0.121	-0.122			1.19
(1.09)	(63.63)***	(0.54)	(-5.40)	(-3..87)***			(0.27)
			Model 4				
0.000	0.824	-0.090	-0.093	-0.290		0.333	0.26
(0.52)	(64.60)***	(-2.34)***	(-4.12)***	(-8.30)***		(10.93)***	(0.60)
			Model 5				
0.000	0.824	0.051	-0.084		-0.107		1.54
(1.24)	(65.86)***	(1.39)	(-3.35)***		(-3.77)***		(0.21)
			Model 6				
0.000	0.850	-0.010	-0.260		-0.210	0.290	0.79
(0.89)	(66.70)***	(-0.27)	(-1.01)		(-6.94)***	(9.98)***	(0.37)

***, **, and *: statistical significance levels at the 1%, 5%, and 10%, respectively.

Panel B: NSC stocks

λ_0	λ_M	λ_S	λ_H	λ_L	λ_D	λ_{NS}	
			Model 1				J-test
0.001	0.793	0.032	0.062				3.37
(1.84)	(57.24)***	(0.78)	(2.49)***				(0.06)
			Model 2				
0.000	0.818	0.008	0.180			0.707	1.52
(1.23)	(61.18)***	(0.22)	(7.33)***			(22.93)***	(0.21)
			Model 3				
0.001	0.830	0.111	0.038	0.452			3.75
(1.94)*	(58.92)***	(2.69)***	(1.54)	(12.93)***			(0.05)
			Model 4				
0.000	0.854	-0.096	0.089	0.135		0.135	0.91
(0.96)	(60.97)***	(-2.27)**	(3.62)***	(18.68)***		(3.50)***	(0.33)
			Model 5				
0.000	0.783	-0.003	-0.083		0.357		2.18
(1.48)	(56.60)***	(-0.08)	(-2.93)***		(11.27)***		(0.13)
			Model 6				
0.000	0.841	-0.135	0.043		0.130	0.641	0.61
(0.78)	(60.06)***	(-3.28)***	(1.54)		(3.92)***	(19.84)***	(0.43)

***, **, and *: statistical significance levels at the 1%, 5%, and 10%, respectively.

Note: The GMM estimations use Hansen's (1982) optimal weighting matrix. The tests are performed on the excess returns of SC (Panel A) and NSC (Panel B) individual firms. Independent variables are: λ_0 the regression intercept; λ_M, λ_S, λ_H, λ_C,λ_D and λ_L are the risk premiums associated market (r_M-r_f), size (*SMB*), B/M (*HML*), SC risk factor (*NSMSC*), leverage (*LEV*) and default risk (*DEFZ*), repectively. Sample period: from July 2005 to June 2024 (16.772 observations for Panel A, 18.825 observations for Panel B). Slopes (z-statistics in parentheses) and the J-test are presented for each panel.

4.3. The SC Risk Factor and Innovations in State Variables

Table 11 shows the results of regressing each of the five innovations series on market, SMB, HML and NSMSC. The SC factor is negatively correlated with $\hat{\varepsilon}_t^{TERM}$ (-0.433) and the coefficient is significant at 10% level. The term spread, used as proxy for business conditions, is considered as the one of the best indicators that can predict recessions and economic recoveries (Naifar, 2016). The relationship between the NSMSC factor and term spread is in line with an ICAPM framework, as it can predict changes in the investment opportunities. The result suggests a risk-based justification for the SC risk factor and corroborates our hypothesis (H1).

Otherwise, Petkova (2006) points out that positive shocks to the term spread are associated with bad business conditions, while negative shocks indicated economic recovery. Accordingly, a possible explanation for the negative relation between the innovation in TERM and SC factor could be that a deterioration in the economic environment has a stronger adverse effect on NSC stock returns than on those of SC ones. Consequently, it is possible to assume that SC assets are less vulnerable to poor economic condition. This observation is consistent with NSMSC as a measure of distress risk. The hypothesis (H2) is supported.

Table 11 also shows that the SMB and HML factors reflect fundamental economic risks. Specifically, the SMB factor is significantly associated with innovations in inflation rate, while the HML factor is significantly associated with innovations in default spread. There was already evidence of this in FF (1996) and Leite et al. (2020).

Overall, although the R^2 values are low, it may be that only the information in SMB, HML and NSMSC factors that is correlated with the state variables matters for asset pricing. Vassalou (2003) and Petkova (2006) reach similar conclusions.

Table 11.
The Relations between Innovations in State Variables and the Market, SMB, HML and NSMSC

Dependent variable	c_0	c_1	c_2	c_3	c_4	R^2(%)
$\hat{\varepsilon}_t^{TERM}$	0.000 (0.14)	0.088 (0.91)	-0.351 (-1.18)	0.122 (0.74)	-0.499 (-1.70)*	0.04
$\hat{\varepsilon}_t^{DIV}$	-0.003 (-1.92)*	0.121 (0.63)	0.425 (1.49)	-0.038 (-0.52)	0.415 (1.06)	0.05
$\hat{\varepsilon}_t^{DEF}$	0.001 (0.49)	-0.428 (-3.12)***	0.434 (1.56)	-0.287 (-1.71)*	0.030 (0.12)	-1.86
$\hat{\varepsilon}_t^{INF}$	-0.000 (-0.16)	0.101 (1.11°	-0.051 (-0.19)	0.577 (3.20)***	-0.203 (-0.73)	11.46
$\hat{\varepsilon}_t^{ST}$	-0.001 (-0.40)	0.131 (1.17)	0.065 (0.23)	0.093 (0.50)	0.152 (0.65)	0.02

***, **, and *: statistical significance levels at the 1%, 5%, and 10%, respectively.

Note: This table reports time series regression results of innovations variables on the market factor, the size factor, the value factor and SC risk factor. Dependent variables: Innovations in the term spread ε^{TERM}, Innovations the dividend yield ε^{DIV}, Innovations in the default spread ε^{DEF}, Innovations in the inflation rate ε^{INF} and Innovations in the 1-month Treasury bill yield ε^{ST}. Sample period: from July 2005 to June 2024 (228 monthly data). Slopes (t-statistics in parentheses) and the R^2adjusted are presented for each innovation variables; standard errors corrected for heteroskedasticity using Newey-West (1980).

4.4. Discussion

We use asset pricing tests to assess if SC risk factor is systematic and if it proxies for financial distress risk. First, the time-series regressions analyse 12 portfolios sorted by size, B/M, and Shariah compliance and two portfolios of distressed and non-distressed firms. The adjusted-R^2 results show that adding the SC risk factor to FF TFM (all adjusted-R^2 values are higher) improves the model's explanatory power. Moreover, evidence shows that the SC risk factor is priced for all examined portfolios. This finding is consistent with Merdad et al. (2015), as they confirm that the SC risk factor captures incremental systematic risk omitted by the market portfolio, SMB and HML in Saudi Arabia market. Similarly, Dharani et al. (2019) and Dharani et al. (2024) report a significant Islamic-effect on stock return variations in India and Indonesia, respectively. Results also show that the coefficient of SC risk factor is positive for distressed firms and negative for non-distressed firms, suggesting that the new factor effectively captures default risk.

The results based on the GMM estimation indicate that NSMSC, LEV and DEFZ factors provide a better explanation of the cross-section of SC and NSC stock returns than HML and SMB factors. Notably, the coefficients of LEV and DEFZ vary in the presence of the SC risk factor, suggesting that the later contains some default-related information shared with the leverage and distress risk factors. This outcome is particularly noteworthy, as the SC factor aligns with variables that have consistently demonstrated their validity in previous studies (Boubaker et al.,2018; Mselmi et al., 2019).

Lastly, we show that the SC risk factor correlates significantly and negatively with innovations in the term spread. This finding is particularly important, as the term spread is the main indicator of economic conditions. The result is consistent with a risk-based explanation of the SC risk factor in the context of ICAPM (Leite et al., 2020).

Overall, we conclude that the contribution of the SC risk factor to explaining stock returns and default risk on the US market remains robust across various tests. One possible interpretation of the relation between NSMSC factor and the distress risk premium may outcomes of the Islamic screening process. First, the exclusion of firms operating in controversial sectors from Islamic portfolios may contribute to reduced financial distress. According to Hussain et al. (2018), such sectors are exposed to economic condition (e.g. gambling, entertainment) or social and political changes (Alcoholic beverages, Tobacco). Second, the exclusion of highly leveraged firms may help mitigate default risk (Peillex et al., 2019). The collapse of major financial institutions such as Lehman Brothers and Goldman Sachs as well-as well-known companies like Enron and WorldCom, due to excessive indebtedness illustrates that leverage is a key determinant of distress risk and a fundamental cause of the global financial crisis (el Alaoui et al., 2017). Finally, limiting the amount of accounts receivable may reduce free cash flow volatility, making SC firms more resilient to financial distress. Therefore, investors demand a higher financial distress risk premium to hold NSC firms in their portfolios.

In terms of managerial implications, our results suggest that the SC risk factor affects the cost of capital and thereby impacts investment decisions and firm valuation. The SC augmented-model provides valuable insights for Islamic finance scholars and professionals, as it helps in more accurately pricing SC assets and highlights the importance of considering financial distress risk protection in evaluating the performance of Islamic investment.

4.5. Robustness Checks to the Subprime and COVID-19 Crises

The previous empirical findings do not clarify whether the results are robust to different market conditions. In what follows, we test the validation of the SC-augmented TFM during the two most recent financial crises: the subprime crisis (August 2007-March 2009) and the Covid-19 pandemic crisis (January 2020-December 2021). Particularly, we verify whether the SC risk factor does not hinge under such stressful periods.

The time-series regression equation is as follows:

$$R_{pt} - RF_t = \alpha_p + \beta_p^{Mup}\tau(RM_t - RF_t) + \beta_p^{S}\ \tau\ SMB_t + \beta_p^{Hup}\tau HML_t + \beta_p^{NSup}\tau\ NSMSC_t + \beta_p^{Mdown}(1-\tau)(RM_t - RF_t) + \beta_p^{Sdown}(1-\tau)SMB_t + \beta_p^{Hdown}((1-\tau)HML_t + \beta_p^{NSdown}(1-\tau)NSMSC_t \quad (11)$$

The dummy variable τ takes a value of one for crisis periods and zero if otherwise. The superscripts *up* and *down* denote the coefficients associated with economic recoveries and recessions, respectively. For the dependent variable, we consider the twelve portfolios defined in section 3.2.1.

Table 12 shows that the portfolio market coefficients β^{Mup} exceed 6 standard errors from zero and vary from 0.748 and 0.972. In the case of crisis periods, the portfolio market coefficients β^{Mdown} are higher than 16 standard errors from zero and vary from 0.884 and 1.055. Moreover, SMB slopes (β_p^{Sup} and β_p^{Sdown}) are associated with size, decreasing from small to big capitalisation in every B/M group. Similarly, HML slopes (β_p^{Hup} and β_p^{Hdown}) are related to B/M ratio, increasing from the lowest B/M quintile to the highest B/M quintile, for both small and big stocks; Regarding the SC risk factor, the coefficients β_p^{NSup} and β_p^{NSdown} are positive for portfolios NSC of firms, while it is negative for portfolios of SC firms.

Overall, the significant loadings on SMB, HML and NSMSC indicate that these factors maintain strong explanatory power for stock returns during both crisis and non-crisis periods. Thus, it is not surprising to observe a large adjusted R-squared ranging from 75.1% to 91.9%. This finding is inconsistent with Horvath & Wang (2021) who find that the R^2 of the five-factor model decreases during crisis period.

To further support the idea that our results do not depend on any specific sample period, Table 13 estimates the model 11 for distressed et non-distressed portfolios. We find that both the HML factor and the SC factor are significantly priced, with premiums that do not differ much from the baseline results. Indeed, β_p^{Hup}, β_p^{Hdown}, β_p^{NSup} and β_p^{NSdown} tend to be negative (positive) and statistically significant for the portfolios of (non)-distressed firms. Previous studies (Pereira & Rua, 2018; Vassalou, 2003; Cochrane, 2001) suggest that the stability of risk factor coefficients over time reflects the robustness of an asset pricing model and indicates its ability to capture fundamental risks in economy.

Table 12.
Time-Series Regression Results of Twelve Sorted Portfolios Across Different Economic Conditions

	α	β_M^{up}	β_S^{up}	β_H^{up}	β_{NS}^{up}	β_M^{down}	β_S^{down}	β_H^{down}	β_{NS}^{down}	Adj-R^2	F-stat
SHNS	-0.000 (-0.51)	0.838 (6.80)***	0.607 (3.76)***	0.501 (10.64)***	0.706 (6.09)***	1.024 (23.30)***	0.646 (4.42)***	0.529 (3.98)***	0.778 (6.07)***	0.919	322.37***
SHSC	0.001 (0.77)	0.878 (6.83)***	0.670 (3.60)***	0.543 (5.56)***	-0.508 (-2.86)***	0.952 (13.55)***	0.463 (3.27)***	0.590 (2.92)***	-0.548 (-2.13)***	0.844	154.28***
SMNS	0.000 (0.33)	0.822 (6.97)***	0.509 (3.81)***	-0.006 (-0.16)	0.138 (1.07)	0.945 (30.43)***	0.278 (0.85)	-0.238 (-1.77)	0.579 (5.56)**	0.861	175.6***
SMSC	-0.002 (-2.01)***	0.839 (6.46)***	0.491 (2.96)***	-0.244 (-4.71)***	-0.528 (-4.29)***	1.021 (19.96)***	0.438 (3.45)***	-0.022 (-0.23)	-0.265 (-2.82)***	0.893	227.13***
SLNS	-0.001 (-1.08)	0.835 (6.25)***	1.109 (6.86)***	-0.541 (-6.30)***	0.380 (2.60)***	1.091 (18.05)***	0.272 (1.46)	-0.457 (-4.06)***	0.617 (3.80)***	0.829	137.18***
SLSC	0.001 (1.58)	0.815 (6.57)***	0.367 (2.18)***	-0.483 (-8.95)***	-0.687 (-6.02)***	0.957 (19.13)***	0.385 (4.83)***	-0.609 (-7.76)***	-0.625 (-4.44)***	0.873	195.82***
BHNS	-0.000 (0.54)	0.756 (6.56)***	-0.295 (-2.14)***	0.373 (6.42)***	0.622 (3.91)***	0.992 (28.04)***	-0.587 (-4.94)	0.246 (3.01)***	0.710 (7.06)***	0.851	162.77***
BHSC	0.000 (0.31)	0.948 (6.30)***	-0.494 (-2.14)***	0.476 (6.05)***	-0.614 (-3.99)***	1.055 (19.92)***	-0.795 (-3.63)***	0.638 (5.25)***	-0.555 (-4.10)***	0.841	149.86***
BMNS	-0.000 (-0.024)	0.803 (6.33)***	-0.334 (-2.18)***	0.071 (1.18)	0.104 (0.94)	0.884 (16.75)***	-0.701 (-7.94)***	0.051 (0.43)	0.582 (4.14)***	0.808	119.98***
BMSC	-0.000 (-0.81)	0.748 (7.15)***	-0.130 (-1.12)	-0.070 (-1.89)	-0.724 (-8.02)***	0.941 (31.12)***	-0.500 (-4.01)***	-0.214 (-2.81)***	-0.193 (-2.05)*	0.876	200.96***
BLNS	0.001 (0.87)	0.972 (6.66)***	-0.840 (-2.68)***	-0.629 (-5.87)***	0.748 (3.12)***	1.055 (27.47)***	-0.423 (-3.30)***	-0.339 (-4.40)***	0.468 (2.69)***	0.751	86.01***
BLSC	-0.001 (-1.15)	0.798 (6.68)***	-0.148 (-0.98)	-0.652 (-10.22)***	-0.436 (-4.46)***	0.993 (31.92)***	-0.506 (-3.95)***	-0.589 (-10.06)***	-0.275 (-3.60)***	0.866	183.99***

***, **, and *: statistical significance levels at the 1%, 5%, and 10%, respectively.

Note: This table reports the results from the SC-augmented TFM across different economic conditions. Dependent variables: 12 excess return portfolios created by size (small and big), B/M (low and high), and SC status (SC and NSC). Independent variables: RM–RF, SMB, HML and NSMSC. *up* and *down* denote the coefficients associated with economic recoveries and recessions, respectively. Sample period: July 2005 to June 2024 (228 monthly returns). Slopes (t-statistics in parentheses), adjusted R^2, and F-test are presented for each portfolio; standard errors corrected for heteroskedasticity using Newey-West (1980).

Table 13.
Time-Series Regression Results of the Portfolios of Distressed Firms (LZ) and Non-Distressed Firms (HZ) Across Different Economic Conditions 2005-2024

$$R_{pt} - RF_t = \alpha_p + \beta_p^{Mup}\tau(RM_t - RF_t) + \beta_p^{S}\ \tau\ SMB_t + \beta_p^{Hup}\tau HML_t + \beta_p^{NSup}\tau\ NSMSC_t + \beta_p^{Mdown}(1-\tau)(RM_t - RF_t) + \beta_p^{Sdown}(1-\tau)SMB_t + \beta_p^{Hdown}((1-\tau)HML_t + \beta_p^{NSdown}(1-\tau)NSMSC_t$$

	α	β_M^{up}	β_S^{up}	β_H^{up}	β_{NS}^{up}	β_M^{down}	β_S^{down}	β_H^{down}	β_{NS}^{down}	Adj-R^2	F-stat
LZ	-0.001 (-0.75)	1.615 (3.10)***	-0.526 (-1.02)	0.459 (5.91)***	0.791 (2.46)***	1.027 (58.96)***	-0.003 (-0.02)	0.331 (4.28)***	0.408 (4.06)***	0.667	57.48***
HZ	0.000 (0.67)	0.819 (6.79)***	0.096 (0.78)	-0.183 (-6.43)***	-0.274 (-3.30)***	0.984 (51.78)***	-1.104 (-1.04)	-0.243 (-5.08)***	-0.213 (-3.12)***	0.923	342.61***

***, **, and *: statistical significance levels at the 1%, 5%, and 10%, respectively.

This table reports the results from the SC-augmented TFM across different economic conditions. Dependent variables: 2 excess returns portfolios of non-distressed (HZ) and distressed (LZ) firms. Independent variables: RM–RF, SM B, HML and NSMSC. Sample period: July 2005 to June 2024 (228 monthly returns). *up* and *down* denote the coefficients associated with economic recoveries and recessions, respectively. Slopes (t-statistics in parentheses), adjusted R^2, and F-test are presented for each portfolio; standard errors corrected for heteroskedasticity using Newey-West (1980).

V. CONCLUSION AND RECOMMENDATION

This paper has attempted to provide a risk-based interpretation of the SC risk factor. To do so, we have subjected the new factor to the same scrutiny that the FF factors have undergone. More specifically, we have investigated whether the SC factor is systematic and whether it is related to distress risk. The first empirical findings from time-series regressions, show that the SC-augmented TFM explains the returns on 12 portfolios formed by size, B/M and shariah compliance better than the FF TFM. Moreover, the return variations of distressed and non-distressed portfolios are better explained by the NSMSC factor than by the HML and SMB factors. Furthermore, the cross-sectional estimation results provide evidence on the role of the SC risk factor in the pricing of the stock returns, even after controlling for additional risk factors, namely the leverage and distress risk premium. In a third set of results, we find that the SC factor significantly correlates with innovation in term spread, which is in line with ICAPM explanation.

In a nutshell, this paper provides empirical support for the SC risk factor as a systematic risk, relating it to financial distress and economic risks. It demonstrates that investing in NSC firms does yield higher expected returns as compensation for the higher distress risk. This finding confirms that Shariah screening criteria help dampen distress risk by excluding highly leveraged firms and those with excessive accounts receivable, which are expected to be more exposed to interest rate and cash flow volatility. Also, Islamic companies avoid impermissible activities that are often sensitive to economic or regulatory shocks.

Our findings have powerful implications and provide a couple of key takeaways from practitioner's perspective. First, they enhance the accurate pricing of SC assets and improve the understanding of the nature of observed return differences between SC and NSC firms. Second, this analysis broadens the scope of how Islamic investment contributes to financial performance by properly accounting for distress risk hedging. Policymakers could use our findings to assess whether developing a regulatory environment aligned with Islamic finance principles could help stabilize financial markets. This is especially pertinent in the U.S. context, as the number of bankrupt firms increased by 40.4% between March 2023 and March 2024[4].

Regarding research limitations, future studies could compare the US case with GCC markets where Islamic finance is more developed. Additionally, testing the SC risk factor with other risk factors and under different economic conditions would further validate its role as a systematic risk.

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APPENDIX

Table A.1.
Augmented Dickey–Fuller Stationarity Test

Dependent variables

		NSC			SC		
		Book-to-market					
		H	M	L	H	M	L
SIZE	S	-6.61	-6.75	-6.54	-6.76	-7.09	-7.12
	B	-7.00	-6.90	-6.57	-7.85	-6.92	-6.96

Independent Variables

Rm	SMB	HML	CMI
-6.99	-6.14	-6.25	-6.08

Table A.1 reports the results of the Augmented Dickey–Fuller stationarity test. The test was performed with a trend and a constant, using three lags. The MacKinnon critical value for rejecting the unit root hypothesis at the 1% significance level is –3.99. The results reject the unit root hypothesis with trend, indicating that all the time series examined are stationary.

Table A.2.
Residual Homoscedasticity White Test

		NSC			SC		
		Book-to-market					
		H	M	L	H	M	L
		LMw					
Size	S	20.85	14.21	19.16	14.03	20.70	22.10
	B	17.37	18.89	18.58	19.61	15.55	17.92
		p.c					
Size	S	0.00	0.00	0.00	0.00	0.00	0.00
	B	0.00	0.00	0.00	0.00	0.00	0.00

The problem of heteroscedasticity is tested through residual versus fitted values plot, White's test for homoscedasticity. As shown in Table 2, results White's test for homoscedasticity indicate that the null hypothesis of homoscedasticity is rejected as the p-values of the test are found to be smaller than 0.05, suggesting that heteroscedasticity is present. The White (1980) and Newey–West (1987) tests solve heteroscedasticity problem by adjusting the statistical significance of the coefficients.

Table A.3.
Residual Autocorrelation Breusch–Godfrey Test

		NSC			SC		
		Book-to-market					
		H	M	L	H	M	L
		LM_{BG}					
Size	S	0.44	1.07	0.25	0.52	0.98	0.10
	B	0.10	0.02	0.14	0.13	1.69	0.66
		p.c					
Size	S	0.64	0.34	0.77	0.59	0.37	0.89
	B	0.89	0.86	0.18	0.97	0.87	0.51

Breusch–Godfrey/LM test for autocorrelation are used to check the assumption of serial correlation. Table 3 shows that the null hypothesis is accepted, suggesting the absence of serial correlation.

Table A.4.
Residual Normality Jarque–Bera Test

		NSC			SC		
		Book-to-market					
		H	M	L	H	M	L
		JB					
SIZE	S	13247	2658.26	1174.24	268.78	10930.97	8238.53
	B	6331.27	4035.02	637.74	5460.48	10195	14203.81
		p.c					
SIZE	S	0.00	0.00	0.00	0.00	0.00	0.00
	B	0.00	0.00	0.00	0.00	0.00	0.00

The is used to assess the normality of residuals. Table A.4 reports Jarque–Bera (1984) test results for the twelve time-series regressions. For all models, the null hypothesis of residual normality is rejected.

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