Common Risk Factors in Stock Returns in the MENA Region

Abstract:
Manuscript type: Research paper
Research aims: This paper investigates whether size, value, profitability, investment, momentum and illiquidity are relevant risk factors in the Middle East and North Africa (MENA) region.
Design/ methodology/ approach: Data from January 2007 to December 2015 is used to construct risk factors in the MENA region. To explain the constructed portfolios' excess returns, we use a single factor model and several multifactor models.
Research findings: Findings show that size, value and profitability are the most important factors in applying asset pricing models to the MENA region. Further, most of the models we analyse are not perfectly able to capture the average excess return in our dataset. A seven-factor model seems to perform better than other competing models.
Theoretical contribution/ Originality: This paper is the first to construct the above-mentioned factors in the MENA markets. Second, this study proposes to add risk factors such as momentum and illiquidity to the Fama and French three-factor and five-factor models in the context of the MENA region.
Practitioner/ Policy implication: The findings provide additional important factors that must be considered when investors in the emerging financial markets want to diversify away the risk or achieve higher excess return.
Research limitation/Implications: This study has some limitations, namely, the short dataset period and the analysis of different markets with different levels of development, which may affect the reliability of the data that we obtained.

Keywords: CAPM, Factor Models, Illiquidity Factor, MENA Market
JEL Classification: G12

1. Introduction

Empirical studies find that the Capital Asset Pricing Model (CAPM) has not performed efficiently in the stock market[1]. Therefore, a consensus has arisen among both academics and practitioners that the simple CAPM does not fully capture the cross section of expected stock returns. Earlier studies indicate that a combination of risk factors explains stock excess returns better than a single factor model. This insight has led to the development of multifactor models that use more than one priced risk factor, along with the market factor used in the CAPM. These factors include size and value (Fama & French, 1993), lagged momentum (Jagadeesh & Titman, 1993; Carhart, 1997), profitability and investment (Fama & French, 2015) and illiquidity (Amihud, 2002).

Fama and French (1993) propose a three-factor model to capture stock excess returns. This model has been successful in explaining stock excess returns. However, Brailsford, Gaunt and O'Brien (2012) document that although the Fama and French three-factor model outperforms the CAPM in explaining average stock returns, it does not explain the non-linear relationship between size and returns. Therefore, it is not a complete model, and more factors must be added. Hence, Carhart (1997) extends the three-factor model with another factor: Momentum. Amihud (2002) finds that the illiquidity factor plays an essential role in explaining stock returns. Fama and French (2015) use the profitability factor first introduced by Novy-Marx (2013), along with the investment factor first introduced by Aharoni, Grundy and Zeng (2013), to extend all the previous models to arrive at a new five-factor model. They find that this new model performs well in explaining average excess returns, although it does not fully capture all excess returns. Hou, Xue and Zhang (2015) propose the q-factor model (a four-factor model) which also includes the profitability and investment factors in addition to the market and size factors. Their findings show that the q-factor model outperforms the Fama and French (1993) and Carhart (1997) models in explaining many market anomalies.

Several studies have highlighted the importance of the risk factors mentioned above mainly for the US and other developed markets. In turn, emerging markets have not been studied in the same level of detail although emerging stock markets have important role in the world portfolio, and the importance of such economies and stock markets are constantly increasing (Hanauer & Linhart, 2015).

This study is conducted in emerging markets, specifically in the Middle East and North Africa (MENA) region. The MENA markets are less developed than other emerging regions such as emerging Asia and Latin America. Moreover, the MENA stock markets are generally small, relatively illiquid, poorly transparent, and dominated by the banking system (Lagoarde-Segot & Lucey, 2008). In addition, the MENA markets as emerging markets are characterized by additional economic, currency, liquidity, institutional and political risks. These markets can be classified as less efficient markets with a high proportion of small companies that have a fundamental role in asset allocation. These characteristics may raise the question whether the

[1] Banz (1981), Basu (1983) and Fama and French (1992), among others.

risk factors found in developed and other developing markets are also relevant for the MENA equity markets. Since there is no source available that provide risk factors for the MENA region, we have to compute our own. Therefore, this study's aim is to examine the most frequently used risk factors' ability to explain stock excess returns in this region. We analyse the size, value, profitability, investment, momentum and illiquidity effects in this region. The motivations for this research are derived from the main previous discussion about testing alternative asset pricing models that explain stock excess returns and the need to test these factor models using a different dataset.

The main contributions of this paper are the following. First, to the best of our knowledge, this paper is the first to construct the five Fama and French (2015) factors in the MENA markets. Second, this study proposes to add risk factors such as momentum and illiquidity to the three-factor and five-factor models in the context of the MENA region. Third, constructing these factors will be the first step in creating a database for the MENA region similar to that of the Fama and French database. Thus, it will allow future researchers to study the MENA region in more depth in areas such as asset pricing, market efficiency and portfolio performance evaluation. Fourth, it contributes to the literature by using more than one test to compare the performance robustness of models under consideration.

The structure of this paper is as follows. In section 2, we cover the literature review related to the different risk factors and asset pricing models. Section 3 describes the factors and the portfolios construction methods. In section 4, we present the dataset and the variables' definitions. Section 5 presents the findings and discussion. In section 6, we draw the main conclusions.

2. Literature Review

The debate about the factors that affect stock returns has been a fundamental part of modern finance. The basic model of stock returns is the CAPM, which was developed by Treynor (1962), Sharpe (1964), Lintner (1965) and Mossin (1966). According to the CAPM, investors are rewarded for systematic risk that cannot be diversified away.

The market risk factor can be classified as the most important factor, as viewed in the early CAPM-related literature. In addition to the market factor, researchers universally search for factors that may explain the returns of various securities. Factors cannot be easily specified; there is a controversial debate about how to determine the number and the nature of these factors. Ross (1976) develops the Arbitrage Pricing Theory (APT), arguing that expected returns can be determined based on different macroeconomic factors. Unlike the CAPM, the APT does not clearly mention what these factors are, since they are likely to vary over time and across markets.

Rosenberg and Marathe (1976) were among the first to develop multifactor models. Later, in the early 1990s, Fama and French took Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM) as a major motivation for multifactor models. Fama and French (1993, 2015,

2016) propose models including factors such as the market factor, the size factor, the value factor, the investment factor and the profitability factor. The Fama and French models are extended to include Carhart's (1997) momentum factor. These models have become standard models within the finance literature.

Fama and French's (1993) innovative work shows that US stock returns can be explained by factors (the size and the value) other than market risk premium. They document that the market risk premium, size and value play an important role in explaining expected returns. The Fama and French (1993) three-factor model has been studied in many equity markets around the world. The results vary from one study to another. Griffin (2002) examines the Fama and French three-factor model for different countries. He finds that the model performs better on a within-country basis than on a global basis.

Barry, Goldreyer, Lockwood and Rodriguez (2002) study the Fama and French three-factor model in 35 emerging markets. Their results show that the value factor is relevant in all those markets. In turn, the presence of the size effect depends on the method used to calculate the size and inclusion of extreme size values. In a similar sample that includes 32 emerging markets, Van der Hart, Slagter and Dijk (2003) find that both size and value are relevant risk factors. Liu, Stambaugh and Yuan (2018) exclude the smallest 30 per cent of firms, which are valued significantly, to construct the value and the size factors in China market. They find that the model based on this construction method outperform the model that is constructed based on Fama and French (1993) methodology. Further, they argue that their model is able to explain profitability and volatility Chinese anomalies. More recently, Hu, Chen, Shao and Wang (2019) investigate the size and value factors in the cross-section of returns for the Chinese stock market. They find that stock returns are strongly related only to firms' size. They explain these results that contradict some of the previous literature by the short sample period.

The empirical asset pricing researchers propose new factor models to improve the three-factor model performance. Carhart (1997) extends the three-factor model with a fourth factor: momentum. By addressing one of the biggest anomalies, the explanatory power of the Fama and French three-factor model was improved. Carhart's model has been extensively tested in various markets. Jegadeesh and Titman (1993) and Lo and MacKinlay (1990) are the first to document the basic idea of momentum effect. They find that investors can earn profits of approximately one per cent per month if they hold stocks with high returns over the preceding months and sell stocks with low returns over the same time period.

Cakici, Fabozzi and Tan (2013) examine value and momentum effects in 18 emerging stock markets. They confirm the existence of value and momentum effects in all 18 emerging markets except for Eastern Europe (no momentum). Hanauer and Linhart (2015) investigate the Carhart model in four emerging market regions: Latin America, EMEA (Europe, the Middle East and Africa), BRIC (Brazil, Russia, India, and China) and Asia. They find strong evidence for the value effect and weak evidence for the momentum effect in those regions. Blackburn and Cakici (2017) use the CAPM and the Carhart four-factor model to investigate stock returns in Europe, Africa, the Middle East and Asia. They find that the value and momentum are significant risk factors in these four markets for both small and large stocks. They also find that the Carhart four-factor model outperforms the CAPM.

Motivated by the dividend discount valuation model, and based on anomalies not considered by the three-factor and four-factor models, Fama and French (2015) extend the three-factor model by adding both profitability and investment factors. These two factors are real examples of what are universally known as quality factors. Fama and French (2015) find that the new model performs better than the Fama and French (1993) three-factor model. By using international regional data, Fama and French (2017) investigate the power of the five-factor model. They report that the model performance has significant differences in North America, Europe, Asia-Pacific and Japan. Based on the investment CAPM, Hou, Xue and Zhang (2015) propose a four-factor q model which consists of the profitability and investment factors in addition to the market and size factors. They conclude that the q-factor model outperforms the Fama and French (1993) and Carhart (1997) models in explaining many market anomalies. Recently, Hou, Mo, Xue and Zhang (2019) compare alternative asset pricing models including Fama and French (2015) five-factor model and Hou, Xue and Zhang (2015) q-factor model and find the latter model outperforms the former.

More recent studies also analyse a six-factor model including the Fama and French (2015) five factors and a momentum factor (Barillas & Shanken, 2018; Fama & French, 2018). Barillas and Shanken (2018) find that models that include the momentum factor, and value and profitability factors that are updated monthly, dominate both the Fama and French (2015) five-factor model and the Hou, Xue and Zhang (2015) q-factor model. Fama and French (2018) conclude that the performance of a six-factor model that combines small and big stocks to measure value, profitability, and investment, is similar to that of the model without the momentum factor.

In addition to the Fama and French factors and the momentum factor, there are other factors that affect stock returns, including the illiquidity factor. The pioneering studies by Amihud and Mendelson (1986) and Brennan and Subrahmanyam (1996) find that illiquidity is a factor affecting asset pricing. Since the illiquidity is found to be a fundamental factor that captures stock returns, numerous measures have been used. The illiquidity ratio is one frequently used measure, following Amihud (2002). More recently, additional studies analysing illiquidity as a risk factor have been published. The basis for most studies was the CAPM, the Fama and French three-factor model and recently, the Fama and French five-factor model. Generally, most of the studies on illiquidity effects have been conducted in developed markets. Dey (2005) uses the turnover ratio as a measure of illiquidity to study the determinants of returns variations in 49 global markets. The results show a positive and significant relationship between return and illiquidity only for emerging markets. In contrast, Rouwenhorst (1999) finds that average stock returns in emerging markets are not affected by stock turnover as a measure of illiquidity. Studies by Hearn (2009) on small and illiquid East African markets and by Hearn and Piesse (2010) on a larger cross section of African markets examine the illiquidity, market, value, and size factors. They find that in those markets, relevant factors include illiquidity, market, value and size.

We conclude that the findings of previous studies for emerging markets are mixed. In addition, there is limited evidence on the performance of these asset pricing models in the MENA region. Although the Fama and French three-factor model is analysed in a few studies, including some of the MENA countries, to the best of our knowledge, no studies analyse either the five-factor model or the six-factor-momentum model in the MENA region. Moreover, no study analyses a six-factor-illiquidity and a seven-factor model in any equity market. The scarce studies in this region may be explained by the lack of comprehensive, high-quality accounting data. However, with the development and increasing importance of this region, this gap in terms of research must be filled. Therefore, the main aim of this study is to contribute to the literature on empirical asset pricing by analysing a new and different dataset. The fact that the MENA region is composed of equity markets characterised by different levels of development and by political and economic instability makes it an interesting region to analyse whether the factors that have been found as relevant in other markets are also relevant for the MENA markets.

3. Methods

In this research, we use the time-series estimation method to evaluate alternative asset pricing models. In addition to the CAPM, we analyse the well-known Fama and French (1993) three-factor model, the Carhart (1997) four-factor model and the Fama and French (2015) five-factor factor model. We also analyse alternative factor models, namely, a four-factor- illiquidity model, a six-factor-illiquidity model, a six-factor-momentum model, and finally, a seven-factor model. Hence, the first step is to examine these factors' abilities to explain portfolio excess returns. The second step is to determine the best combination of these factors to be used to explain average excess return in the MENA region.

3.1. The factors construction

To construct the factors, we use the Fama and French (1993, 2015) methodology and form six portfolios. These portfolios are constructed in December for each year[2]. We assume that these hypothetical portfolios are held without trading for the next twelve months to minimize transaction costs that would be associated with managing these portfolios. Since we do not have access to the MENA indices constituents, we cannot use the median of an existing index. To remedy this issue, we adopt the median of the market values of the companies in the dataset. In this case, the size breakpoints can distinguish the large from the small stocks. In the same way, the breakpoints of the B/M ratio, profitability (OP) and investment (INV), lagged momentum (MOM) and illiquidity (ILLIQ) can divide the sample into different groups. The factors that are constructed based on this methodology are called small minus big (SMB), high minus low (HML), conservative minus aggressive (CMA), robust minus weak (RMW), winner minus loser (WML) and illiquid minus liquid (ILML).

[2] To avoid the look-ahead bias, we lagged our data one year to be sure that at the end of each December, we have all the required variables.

In December of each year, all stocks are sorted and grouped into two size portfolios. The first portfolio is the small (S) portfolio, which is composed of stocks with the lowest 50 per cent of the region's total market capitalization (MC). The second portfolio is the big (B) portfolio, which is composed of stocks with the highest 50 per cent of the region's total MC[3]. Independently, all stocks meeting the selection criteria are sorted based on their B/M ratio and grouped into three value portfolios. We determine the lowest 30 per cent (growth (G)), the middle 40 per cent (neutral (N)), and the top 30 per cent (value (V)) breakpoints for B/M. Based on the intersection of size and B/M quantiles, we construct six portfolios: SG, SN, SV, BG, BN, and BV. These portfolios are held for the next twelve months, and the value-weighted returns are calculated for the period from December year t to December year t+1. We repeat the same procedures at the end of the holding period. Each year, the six portfolios are rebalanced again based on the new values of the MC and B/M ratio. In the 2×3 sorts, the SMB=1/3×(SV+SN+SG)–1/3×(BV+BN+BG). HML=1/2×(SV+BV)–1/2×(SG+BG).

We construct the OP factor in a similar way. We determine the lowest 30 per cent (Weak (W)), the middle 40 per cent (Neutral (N)), and the top 30 per cent (Robust (R)) breakpoints for the OP variable and apply these breakpoints to large and small stocks. From the intersection of the relevant size and OP quantiles, we construct six portfolios: SR, SN_{OP}, SW, BR, BN_{OP}, and BW. We also determine the lowest 30 per cent (Conservative (C)), the middle 40 per cent (Neutral (N)), and the top 30 per cent (Aggressive (A)) breakpoints for the INV variable and apply these breakpoints to large and small stocks. From the intersection of the relevant size and INV quantiles, we construct six portfolios: SC, SN_{INV}, SA, BC, BN_{INV}, and BA. All these OP and INV portfolios are held for the next twelve months, and the value-weighted returns are calculated on the portfolios for the period from December year t to December year t+1. In the 2×3 size-OP sorts, the RMW=1/2×(SR+BR)-1/2×(SW+BW). In the 2×3 size-INV sorts, CMA=1/2×(SC+BC)-1/2×(SA+BA).

In the 2×3 size-B/M sorts, 2×3 size-OP sorts and 2×3 size-INV sorts, SMB is the average return on the nine small stock portfolios minus the average return on the nine large stock portfolios.

$$SMB_{B/M}=1/3\times(SV+SN+SG)-1/3\times(BV+BN+BG)$$

$$SMB_{OP}=1/3\times(SR+SN_{OP}+SW)-1/3\times(BR+BN_{OP}+BW)$$

$$SMB_{INV}=1/3\times(SC+SN_{INV}+SA)-1/3\times(BC+BN_{INV}+BA)$$

$$SMB=1/3\times(SMB_{B/M}+SMB_{OP}+SMB_{INV})$$

Based on size and MOM, we further construct six portfolios. At the end of each month, all stocks are sorted and grouped into two size portfolios. Independently, we sort on the MOM and determine the lowest 30 per cent (Losers (L)), the middle 40 per cent (Neutral (N_{mom})), and the top 30 per cent (Winners (W)). The intersection of the independent sorts on size and MOM produces six portfolios: SL, SN_{MOM}, SW, BL, BN_{MOM}, and BW. The value-weighted monthly

[3] We also applied different breakpoints for our sample (e.g., top 30 per cent (10 per cent) and bottom 70 per cent (90 per cent)), to see if there is any effect of the breakpoint on the results. We obtain similar results for the different breakpoints.

returns on portfolios are computed each month from December t to December t+1. The WML=1/2×(SW+BW)-1/2×(SL+BL).

To construct the ILLIQ factor, a similar procedure is used. For both small and large size portfolios, the stocks are sorted into three separated ILLIQ-ranked portfolios: the lowest 30 per cent (Liquid, (L)), middle 40 per cent (Neutral, (N_{ILLIQ})), and the highest 30 per cent (Illiquid, (IL)). This generates six size-ILLIQ portfolios: SIL, SN_{ILLIQ}, SL, BIL, BN_{ILLIQ}, and BL. Low values of the ILLIQ measure indicate high liquidity, whereas high values of the measure indicate high ILLIQ. The value-weighted monthly returns on the portfolios are computed each month from December t to December t+1. ILML=1/2×(SIL+BIL)–1/2×(SL+BL).

3.2. Portfolio construction

This sub-section describes the construction of the portfolios used as dependent variables. We construct 25 portfolios based on the size and the B/M equity ratio. The 25 size-B/M portfolios are formed in the same way as the six size-B/M portfolios described above. In December of each year, we allocate the MENA stocks to five size portfolios based on the MC and independently to five value portfolios based on the B/M. From the intersections of the size and the value portfolios, we construct 25 portfolios. In the same way, we construct 25 portfolios based on size and OP variable, 25 portfolios based on size and INV variable, and 25 portfolios based on size and MOM variable. Then, we calculate the value-weighted monthly returns on the portfolios from December t to Decembert+1.

To examine possible ILLIQ effects, we sort stocks into three portfolios based on ILLIQ. Independently, we sort stocks into three portfolios according to size. From the intersections of the size and the ILLIQ portfolios, we construct nine portfolios. The value-weighted monthly returns are calculated on the portfolios from December t to December t+1. In this set, we construct only nine portfolios, because the number of stocks that have information on the ILLIQ ratio is small.

3.3. Model tests

Using the excess returns on the portfolios and the factor returns described above, we test different asset pricing models for the MENA region. These tests are performed using the time-series regression approach, which are represented in Equations (1) to (8).

The CAPM

$$R_{P,t}-R_{ft}= \alpha+\beta(R_{M,t}-R_{ft})+\varepsilon_t \tag{1}$$

The three-factor model

$$R_{P,t}-R_{ft}= \alpha+\beta(R_{M,t}-R_{ft})+s(SMB)+h(HML)+\varepsilon_t \tag{2}$$

The four-ILLIQ model

$$R_{P,t}-R_{ft}= \alpha+\beta(R_{M,t}-R_{ft})+s(SMB)+h(HML)+il(ILML)+\varepsilon_t \tag{3}$$

The four-MOM model

$$R_{P,t}-R_{ft}= \alpha+\beta(R_{M,t}-R_{ft})+s(SMB)+h(HML)+m(WML)+\varepsilon_t \quad (4)$$

The five-factor model

$$R_{P,t}-R_{ft}=\alpha+\beta(R_{M,t}-R_{ft})+s(SMB)+h(HML)+c(CMA)+r(RMW)+\varepsilon_t \quad (5)$$

The six-ILLIQ model

$$R_{P,t}-R_{ft}=\alpha+\beta(R_{M,t}-R_{ft})+s(SMB)+h(HML)+c(CMA)+r(RMW)+il(ILML)+\varepsilon_t \quad (6)$$

The six-MOM model

$$R_{P,t}-R_{ft}=\alpha+\beta(R_{M,t}-R_{ft})+s(SMB)+h(HML)+c(CMA)+r(RMW)+m(WML)+\varepsilon_t \quad (7)$$

The seven-factor model

$$R_{P,t}-R_{ft}=\alpha+\beta(R_{M,t}-R_{ft})+s(SMB)+h(HML)+c(CMA)+r(RMW)+m(WML)+il(ILML)+\varepsilon_t \quad (8)$$

In the above Equations,
$R_{P,t}-R_{ft}$ is the continuously compounded return on the stock portfolio p in excess of the risk-free rate,
$R_{M,t}-R_{ft}$ is the continuously compounded return on a market benchmark in excess of the risk-free rate,
SMB is the average return difference between small and large portfolios,
HML is the average return difference between value and growth portfolios,
RMW is the average return difference between robust and weak portfolios,
CMA is the average return difference between conservative and aggressive portfolios,
WML is the average return difference between winner and loser portfolios, and
ILML is the average return difference between illiquid and liquid portfolios.

Five sets of left hand side (LHS) portfolios are used to evaluate each model. We use the Gibbons, Ross and Shanken (1989) test (GRS) to analyse whether the pricing errors of all portfolios in each size sort set are jointly equal to zero. This enables us to evaluate and compare the various models. We run individual Ordinary Least Squares (OLS) regressions to obtain the model parameter estimates. If the model captures all the variation in returns, the intercept α in each model should be zero for all portfolios. In addition to the GRS and the OLS estimates, we report the Akaike information criteria (AIC) of all models and the adjusted R^2 differences between the models. We calculate the average of portfolios' AIC values to find the AIC for each model for each LHS portfolio set. To investigate whether the models' performance is significantly different, we apply the bootstrap method to find the mean adjusted R^2 for each model in each portfolio set and test the difference between the adjusted R^2 for each two models.

4. Data and Variables Definition

4.1. Data

Our dataset is composed of non-financial firms listed on all exchanges of 13 countries in the MENA region. These countries are Bahrain, Egypt, Israel, Jordan, Kuwait, Lebanon, Morocco, Palestine, Oman, Qatar, Saudi Arabia, Tunisia and the United Arab Emirates[4]. We collected the required data from Thomson Reuters DataStream database. The period of analysis is December 2004 through December 2015, but we lost the first two years because of the construction of the INV and MOM factors; therefore, our sample period is from January 2007 to December 2015. The dataset period was selected to have historical data for as long as possible and to have coverage of markets that is as broad as possible. Although few financial markets in the MENA region have available data before 2005, most of the financial markets do not have. The main consideration for this choice is to make sure that the data are available for all markets. We include all non-financial companies[5] that are listed in the MENA exchange markets. Since we cover companies from different countries with different currencies, all data are converted to US dollars.

From our dataset, we select those stocks that have information on MC, and on the following accounting variables: annual revenues, cost of goods sold, interest expenses, selling, general, and administrative expenses, book value of equity, INV tax credit, deferred tax, preferred stocks, total assets, number of outstanding shares, daily total return index, daily number of trading stocks, and daily closing price. We also use monthly total return index (RI) for return calculation. All these variables are used to construct the different factors. These company-accounting items are obtained from the DataStream database. In some cases, we also collect data from company financial reports, obtained through the companies´ websites, and from the official websites of corresponding equity markets[6]. Thus, we use the hand-collected data to enlarge our sample to ensure that we include all the listed non-financial companies. For the risk-free rate, we use the US T-Bill one-month rate because we extract all our data using the US dollar. We obtain these data from the Kenneth French data library. To avoid a possible survivorship bias, delisted stocks are included until they disappear. In this study, we include only equity-type securities, excluding the preferred shares from the database. Firms with negative book equity and some outliers are excluded[7].

4.2. Variables definition

We use the following data to calculate the required variables for portfolios and factors' construction:

Book Value (BV) is the BV of equity plus balance sheet deferred taxes and investment tax credit minus the BV of preferred stocks. We calculate this variable annually at the end of each fiscal year for each company.

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[4] We based on the United Nations' website to define the MENA countries. Those 13 countries are the only MENA countries that are included on the DataStream and have data.

[5] Banks and insurance companies were excluded.

[6] The majority of the companies in the MENA region use the International Financial Reporting Standards. (Mwaura and Nyaboga, 2011).

[7] Two firms with stock returns equal to or higher than 200 per cent were excluded since this value was very large compared to the other returns.

MC is the closing stock price multiplied by the number of outstanding shares at the end of each year. It is used for computing value-weighted return, size, value and the B/M ratio.

B/M ratio is used to construct portfolios in December of year t, based on the value of the BV of equity for the year t-1, divided by MC at the end of December of year t-1.

OP is used to construct portfolios in December of year t, based on the operating income (measured as annual revenues minus cost of goods sold, selling, general, and administrative expenses) after interest expenses of year t-1 divided by BV of year t-1.

INV is used to construct portfolios in December of year t based on the total assets at the end of year t-1 minus total assets at the end of year t-2, divided by total assets at the end of year t-2.

ILLIQ, following Amihud's (2002) definition, is used to construct portfolios in December of year t, based on the monthly ILLIQ ratio. The daily ILLIQ ratio is measured as the absolute value of daily stock returns divided by daily trading volume (the daily stock price multiplied by the daily number of trading stocks). The monthly ILLIQ ratio is calculated as the average of daily ILLIQ ratio for each stock each month.

MOM, following Jegadeesh and Titman (1993), is the common measure of the past 12 months' cumulative return on the stock, MOM2-12, skipping the most recent month's return to avoid the one-month reversal in stock returns, so the MOM is a stock's cumulative return for t-12 to t-2.

Market return ($R_{M,t}$) is the market return calculated as the equally weighted monthly return of all shares that have the available data plus the negative B/M stocks that we exclude when we construct the factors and the portfolios. We use the simple average to have a more diversified index with a bigger mid-cap base rather than concentrate on the largest companies[8].

Most of the market indices in general use the value-weighted average return for the stocks that are included in the index. The problem is that these market indices are biased by the existence of large and liquid listed companies. In this paper, we decide to use an equally weighted index that concentrates more on the higher growth potential stocks, which are the small and mid-cap stocks. Indeed, most of the stocks in our sample are classified as small and mid-cap stocks. Therefore, we use the equally weighted market portfolio, using all the stocks to limit the effect of the biggest companies on overall portfolio performance.

4.3. Summary statistics for factor returns

[8] The value-weighted index was also used; we notice that there is no huge difference in the results, but the equally weighted index gives higher R^2.

Table 1, Panel A shows summary statistics for factors' returns. The findings show that only HML is statistically significant at the 5 per cent level of confidence. The average HML return is 0.67 per cent per month (t=2.29), with a standard deviation of 3.04 per cent. The value premium is higher for small stocks. The average return for the HML_s is 1.16 per cent per month (t=5.01) with a standard deviation of 2.41 per cent. Therefore, these values suggest the existence of a value premium in the MENA region. Although the size, INV, OP, MOM and ILLIQ effects do not seem to be present in our sample, the factors' premiums are higher for the small stocks.

Panel B of Table 1 shows the correlation matrix between all the factors. The negative correlation between the market and the size can be evidence of a reverse size effect.

Table 1: Summary Statistics for Factors Average Monthly Returns

Panel A: Averages, standard deviations and t-statistics for monthly returns

	Mean	Std dev.	t-statistics
$R_{M,t}$-R_{ft}	0.75	4.31	1.81
SMB	0.24	3.67	0.67
HML	0.67	3.04	2.29
RMW	0.10	2.31	0.46
CMA	-0.14	2.48	-0.61
WML	-1.16	6.98	-1.72
ILML	0.80	6.29	1.31
HML_b	0.18	5.44	0.34
HML_s	1.16	2.41	5.01
RMW_s	0.17	3.74	0.47
RMW_b	0.04	4.30	0.09
CMA_s	0.35	2.09	1.73
CMA_b	-0.64	4.18	-1.58
WML_s	-0.88	5.87	-1.55
WML_b	-1.44	9.76	-1.53
$ILML_s$	1.58	6.42	2.56
$ILML_b$	0.01	11.32	0.00

Panel B: Correlations between different factors

	$R_{M,t}$-R_{ft}	SMB	HML	CMA	RMW	WML	ILML
$R_{M,t}$-R_{ft}	1.00						
SMB	-0.68	1.00					
HML	-0.23	0.39	1.00				
CMA	-0.56	0.52	0.59	1.00			
RMW	0.21	0.01	0.37	0.13	1.00		
WML	0.30	-0.18	0.19	0.09	0.06	1.00	
ILML	-0.56	0.41	0.25	0.49	-0.19	0.04	1.00

Notes: Panel A shows average monthly returns, expressed in percentage (Mean), the standard deviation of the monthly returns (Std. dev.) and the corresponding t-statistics. Panel B shows the correlations between the different factors.

The highest correlation is between the value and INV factors, with a positive value of 0.59, suggesting that the value stocks are conservative stocks more than the growth stocks. The value factor is positively correlated with the ILLIQ factor, documenting that the growth stocks are more liquid than the value stocks. The value factor is also positively correlated with size, OP and MOM factors. MOM is positively correlated with ILLIQ, suggesting that winner stocks are more illiquid than loser stocks. OP is negatively correlated with ILLIQ, suggesting that the more robust portfolios are more liquid. INV is positively correlated with size, value, MOM, OP and ILLIQ. Thus, our results suggest that in the MENA region, small stocks are value, conservative, robust, illiquid and loser stocks.

4.4. Summary statistics for the portfolios' excess returns

This section presents the summary statistics for the LHS different size-sort portfolios. Panel A of Table 2 shows average monthly excess returns and the standard deviations for the 25 size-B/M value-weighted portfolios. Regarding the relationship between size and average excess returns (the size effect), we notice that the stocks in the right column of the size-B/M matrix exhibit a standard size effect; the small-value stocks tend to have higher excess returns than the large-value stocks in the last size quintile. In the left two columns of the size-B/M matrix, the small-growth stock portfolios tend to present lower excess returns compared to the large-growth stock portfolios. In each column of the three right quintiles of B/M, the average excess return falls from small to large stock portfolios.

Therefore, we can say that this may be evidence of a size effect. In terms of the relationship between B/M and average excess returns (the value effect), each size row in Panel A of Table 2 shows that average excess returns increase from low B/M to high B/M stock portfolios. The extreme small stocks in the first row of size quintiles tend to have higher return premiums than the extreme large stocks in the last size quintile. However, in Panel B of Table 2, we observe that average excess returns in all the INV quintiles have a standard size effect. This effect is more robust in the left INV quintile, which includes extremely conservative INV stocks. The smallest portfolio in the conservative INV quintile has the highest excess return of all. Thus, we can say that there is evidence of a size effect on INV portfolios.

Examining the relationship between INV and average excess returns (the INV effect), we observe that the average excess returns in the first and the third rows of size quintiles fall from the portfolios in the left column to the right column. Therefore, the INV effect is not clear in our sample.

Panel C of Table 2 shows that the average excess returns of the size-OP in general decrease with size. We observe that the size effect is more robust in the left column that includes extremely weak OP stocks. Analysing the relationship between OP and average excess returns (the OP effect), each size row in Panel C of Table 2 shows that average excess returns tend to increase in a non-monotonic manner, except for the first size row in which the extremely weak portfolio has a higher return than the extremely robust portfolio. This suggests that there might be an OP effect in our sample, particularly among the large stocks.

Table 2: Summary Statistics for the Different Size-Sort Portfolios Excess Returns

Panel A: Monthly excess return for size-B/M 25 portfolios										
	Low	2	3	4	High	Low	2	3	4	High
Small	0.63	0.63	1.05	1.51	2.15	5.19	3.06	3.42	3.95	5.03
2	-0.49	0.06	0.80	1.22	1.37	5.71	3.87	4.76	5.71	4.44
3	0.02	0.78	0.46	1.00	1.3	4.80	3.80	4.89	5.09	5.89
4	-0.20	0.21	-0.04	0.55	0.72	4.26	4.82	4.38	4.66	5.98

Big	0.78	0.79	0.73	-0.1	1.04	8.16	7.74	4.49	5.38	6.35
Panel B: Monthly excess return for size-INV portfolios										
	Cons.	2	3	4	Agg.	Cons.	2	3	4	Agg.
Small	2.46	1.06	0.49	1.43	1.28	6.54	3.75	2.76	4.97	4.24
2	0.32	0.92	1.50	0.65	0.49	4.42	3.80	4.50	4.55	5.26
3	0.64	1.26	0.83	0.51	0.25	5.10	5.01	4.29	4.16	5.32
4	0.15	-0.05	-0.19	0.44	0.21	3.58	4.29	4.23	4.79	5.42
Big	0.15	0.94	0.60	0.44	0.91	3.64	6.43	5.51	8.00	7.96
Panel C: Monthly excess return for size-OP portfolios										
	Weak	2	3	4	Robust	Weak	2	3	4	Robust
Small	2.37	1.28	0.70	1.16	1.52	6.43	3.85	2.35	3.97	4.75
2	0.29	0.81	1.26	0.88	1.07	4.91	4.22	3.69	5.09	5.82
3	0.82	0.65	0.62	0.34	1.24	5.79	4.51	4.82	4.47	5.59
4	-0.49	0.22	-0.05	0.38	0.23	4.83	5.26	4.07	4.36	4.55
Big	0.34	0.56	0.48	0.58	0.43	6.11	5.65	5.14	5.08	7.67
Panel D: Monthly excess return for size-MOM portfolios										
	Looser	2	3	4	Winner	Looser	2	3	4	Winner
Small	3.28	1.62	0.99	1.03	1.64	10.69	4.56	3.29	4.46	5.54
2	1.43	0.49	0.89	0.08	0.11	6.56	3.75	3.08	0.35	6.07
3	1.36	0.61	0.38	0.17	0.62	7.51	3.42	3.13	3.88	7.67
4	0.88	0.08	0.31	-0.50	0.06	4.61	4.22	4.51	5.97	6.13
Big	0.98	0.06	-0.12	0.07	-0.74	7.01	7.36	5.66	7.82	12.48
Panel E: Monthly excess return for size-ILLIQ portfolios										
	Low	2	High			Low	2	High		
Small	0.25	1.74	2.15			2.81	7.97	5.89		
2	-0.01	1.36	1.75			8.36	9.99	5.93		
Big	-0.79	0.22	0.11			10.86	5.80	3.08		

Notes: This Table reports the mean and standard deviation of the excess returns for the 25 size-B/M, 25 size INV, 25 size-OP, 25 size MOM and 9 size-ILLIQ portfolios.

Panel D of Table 2 shows the patterns in the average excess returns of size-MOM portfolios. In all columns of MOM quintiles, average excess returns fall from small to large stocks. This result is more robust in the last column that includes the winner stocks, and it is smoother for the loser stocks. In relation to the relationship between MOM and average excess returns (the MOM effect), each size row in Panel D of Table 2 shows that average excess returns decrease from the loser to the winner portfolios, suggesting that there is no standard MOM effect in the MENA region.

Panel E of Table 2 shows average excess returns for size-ILLIQ portfolios. In this panel, the standard size effect is clear. The small stock portfolios tend to be riskier than the large stock portfolios but also have higher excess returns. Analysing the relationship between the ILLIQ and average excess returns (the ILLIQ effect), each size row shows that average excess returns increase from low ILLIQ portfolios to high ILLIQ portfolios. This suggests that there might be an ILLIQ effect in the MENA region. This effect appears to be more robust for the smallest size quintile.

5. Findings and discussion

In this section, we test how well each model explains average excess returns on the different portfolios. The objective is to determine which factors capture average stock returns and which is the best model for explaining these portfolios returns in the MENA markets. Using a time-series approach, we estimate and analyse the models expressed in Equations (1) to (8).

5.1. GRS test

Table 3 shows the results of the GRS test and summary statistics for the regressions intercepts for the size-B/M portfolios[9]. Our right-hand side (RHS) factors are the market factor, SMB, HML, CMA, WMR, WML and ILML. We calculate these factors as described in section 3.1. Comparing combinations of these factors enables us to evaluate the best model. To examine the effectiveness of an asset-pricing model, a high value of the GRS statistic is undesirable. A small P-value indicates that we can reject the null hypothesis that all the intercepts are jointly equal to zero.

Since our main interest is to compare the models' relative performance, we compare the average absolute value of regression intercepts |a|, regression average adjusted R^2, intercepts standard deviations S(a), the P-values and the models' unexplained squared Sharpe ratios SR(a) across the models. Lower absolute intercepts, lower intercepts' standard deviations, lower squared Sharpe ratios, higher P-values and higher average adjusted R^2 indicate the better performance of the model.

Table 3 reports that the three-factor model significantly enhances the model performance significantly above the CAPM, as observed by higher R^2, lower GRS, lower S(a) and lower SR(a).

Moreover, both the four-factor models improve on the three-factor model performance, with higher R^2, lower GRS, lower S(a) and lower SR(a). The five-factor model enhances the performance of both the four-factor models, with higher R^2, lower GRS, lower S(a) and lower SR(a). Both the six-factor models perform better than the five-factor model, and the seven-factor model performs better than all the other competing models.

Table 3: GRS Test for Portfolios Formed on Size-B/M

Model	GRS	|a|	R^2	P(GRS)	S(a)	SR(a)
CAPM	3.658	0.527	0.556	0.000	0.322	1.072
Three-	3.144	0.433	0.629	0.000	0.303	1.048
Four-MOM	2.558	0.353	0.640	0.001	0.311	0.994
Four-ILLIQ	3.134	0.431	0.633	0.000	0.309	1.079
Five-	3.076	0.437	0.644	0.000	0.303	1.072

[9] The GRS of the other size sorts present similar results regarding the superiority of the seven-factor model. The results are available upon request.

Six-MOM	2.506	0.349	0.653	0.001	0.309	1.012
Six-ILLIQ	2.967	0.421	0.647	0.000	0.310	1.087
Seven-	2.289	0.328	0.656	0.003	0.319	1.009

Notes: This Table reports summary statistics for regressions of monthly excess returns on portfolios formed on size-B/M. The GRS statistic tests whether all intercepts in the set of 5×5 regressions are zero; |a| is the average absolute value of the intercepts; R^2 is the average adjusted R^2; S(a) is the average standard error of the intercepts; SR(a) is the square of the Sharpe ratio for the intercepts; P(GRS) is the p-value for the GRS statistic.

Therefore, the best model among these eight models is the seven-factor model, with the highest R^2 (0.656), the lowest GRS (2.289), the lowest |a| (0.328), the highest P-value (0.003) and the second lowest SR(a), with a value of 1.009.

Hence, using the GRS test, we conclude that although not all the models under analysis can fully explain the portfolios' excess returns, the seven-factor, the six-factor-ILLIQ, and the four-factor-ILLIQ models are the best-performing models.

5.2. Models performance robustness tests

As an additional analysis, we use the AIC and the differences in the mean adjusted $R^2$to compare the performance of the different models. Table 4 reports the AIC for all models for all LHS portfolio sets. The lowest AIC value is for the seven-factor model in all the LHS sets. Table 5 reports the mean adjusted R^2 that results from the bootstrap method for each asset pricing model considering the portfolios based on the size-B/M sort. From the results of Table 5, we can conclude that the three-factor model adjusted R^2 is significantly different from the CAPM adjusted R^2; since the P-value of the difference is zero, we thus reject the null hypothesis that the difference between the two models' adjusted R^2 is zero. The five-factor model adjusted R^2 is also significantly different from the three-factor model adjusted R^2 and the four-factor-ILLIQ model adjusted R^2 but not significantly different from the Carhart four-factor model adjusted R^2. The seven-factor model adjusted R^2 is significantly different from all other models' adjusted R^2.

Table 4: AIC for the Alternative Models for Portfolios Formed on Different Size-Sort

Model	Size-B/M	Size-INV	Size-OP	Size-MOM	Size-ILLIQ
CAPM	555	545	550	665	717
Three-	538	531	535	591	623
Four-MOM	534	529	533	560	621
Four-ILLIQ	537	531	535	591	614
Five-	535	526	529	590	623
Six-MOM	532	524	527	560	621
Six-ILLIQ	535	526	529	591	613
Seven-	532	524	527	561	611

Notes: The Table reports the AIC for the different models. The AIC is the average of all portfolios' AIC for each model for each size sort set.

Table 5: Differences in the Mean Adjusted $R^2$of the Alternative Asset Pricing Models for the Size-B/M Portfolios

Variable	CAPM	Three-	Four-MOM	Four-ILLIQ	Five-	Six-MOM	Six-ILLIQ	Seven-
Mean R^2	0.56	0.64	0.65	0.65	0.66	0.67	0.67	0.68
CAPM	-	0.08	0.09	0.09	0.10	0.11	0.11	0.12

	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Three-	-	0.01	0.01	0.02	0.03	0.03	0.04
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Factor-MOM		-	-0.01	0.01	0.02	0.01	0.03
			(0.14)	(0.25)	(0.00)	(0.03)	(0.00)
Four-ILLIQ			-	0.01	0.03	0.02	0.03
				(0.00)	(0.00)	(0.00)	(0.00)
Five-				-	0.01	0.01	0.02
					(0.00)	(0.00)	(0.00)
Six-MOM					-	-0.01	0.01
						(0.11)	(0.00)
Six-ILLIQ						-	0.01
							(0.00)

Notes: This Table reports the mean adjusted R^2 for each model considering the portfolios resulting from the size-B/M sort and the difference between the adjusted R^2 for each two models and the corresponding p-value (reported in parentheses) on the test if the difference is equal to zero, obtained using the bootstrap method.

Therefore, Table 5 confirms the GRS and the AIC results that the performance difference between the models, in general, is significant. Moreover, it also confirms that the seven-factor model is the superior model.

5.3. Regression details analysis

To obtain a deep understanding of the performance of each model, we examine and discuss the regression estimates, specifically, intercepts and factors' slopes and their associated t-statistics.

Table 6 summarizes the intercepts and the factors' slopes for the seven-factor model considering the size-B/M portfolios[10]. The results for this model show that several of the analysed portfolios have intercepts that are insignificantly different from zero. Insignificant intercepts show that the model can explain the stock returns. This result is confirmed by the GRS test, AIC analysis and the adjusted R^2 differences analysis presented above. The portfolios' slopes are different from one factor to another. The market slopes are high for most of the portfolios, and some of them are higher than one. The significant market slopes indicate that the market risk factor is a relevant risk factor in the MENA region. The SMB slopes are statistically positive for all the small stocks; this means that there is a standard size effect among those small stock portfolios.

Table 6: Seven-Factor Model Regressions Estimates for the 25 Size-B/M Portfolios

	Low	2	3	4	High	Low	2	3	4	High
			a					t(a)		
Small	-0.17	-0.09	0.24	0.84	0.94	-0.34	-0.41	0.91	2.57	2.46
1	-1.35	-0.53	0.01	0.06	0.12	-3.11	-1.75	0.02	0.21	0.51
2	-0.22	0.39	-0.33	-0.03	-0.06	-0.60	1.61	-1.46	-0.10	-0.22
3	-0.46	0.02	-0.34	-0.18	0.10	-2.02	0.09	-1.65	-0.81	0.30
Big	0.12	0.25	0.47	-0.21	1.03	0.36	0.63	2.01	-0.64	2.33
			b					t(b)		

[10] The regression details of other portfolio sets and other models are available upon request.

Small	0.90	0.62	0.69	0.58	1.05	4.65	5.66	5.76	5.84	7.71
1	1.03	0.71	0.94	1.26	0.95	5.75	7.66	7.53	11.50	11.67
2	0.56	0.52	0.93	0.94	1.26	5.37	5.59	11.99	7.97	10.98
3	0.69	0.61	0.69	0.75	0.88	6.83	7.54	9.24	9.32	5.64
Big	1.36	1.02	0.56	0.61	0.23	10.38	4.10	6.13	6.19	1.61
			s					t(s)		
Small	0.54	0.33	0.25	0.34	0.49	2.98	2.85	1.73	2.91	4.03
1	0.41	0.16	0.39	0.26	0.30	2.28	1.34	3.40	2.14	2.79
2	0.08	-0.02	0.13	0.24	0.05	0.77	-0.14	1.65	2.30	0.32
3	0.03	-0.25	-0.20	-0.19	-0.47	0.42	-2.35	-2.37	-2.26	-2.40
Big	-0.73	-0.80	-0.54	-0.67	-1.53	-7.07	-3.98	-8.42	-6.77	-10.61
			h					t(h)		
Small	-0.29	0.04	0.13	0.10	0.12	-1.66	0.35	1.45	0.84	1.01
1	-0.24	0.00	-0.04	0.05	0.37	-1.74	-0.04	-0.29	0.36	3.87
2	-0.32	0.00	0.00	0.12	0.52	-2.87	-0.04	-0.02	1.27	3.33
3	-0.30	-0.16	-0.11	0.33	0.60	-4.11	-2.16	-1.36	4.68	3.66
Big	-0.45	-0.20	0.05	0.31	0.95	-4.21	-1.05	0.67	3.20	5.40
			c					t(c)		
Small	0.36	-0.05	0.18	-0.36	0.13	1.57	-0.36	1.01	-2.43	0.69
1	-0.06	-0.07	-0.04	-0.13	-0.19	-0.29	-0.39	-0.28	-0.68	-1.56
2	-0.12	-0.24	-0.39	-0.32	0.04	-0.73	-1.71	-2.07	-1.56	0.23
3	0.15	0.09	-0.01	-0.59	0.00	1.40	0.62	-0.08	-4.19	0.02
Big	0.05	-0.49	-0.28	0.01	0.17	0.30	-2.19	-2.52	0.08	0.97
			r					t(r)		
Small	0.23	-0.01	-0.01	0.12	0.09	1.06	-0.05	-0.07	0.98	0.75
1	0.13	-0.37	-0.11	-0.19	0.17	0.63	-2.91	-0.94	-1.85	1.91
2	0.32	0.10	-0.05	-0.02	0.20	2.70	0.95	-0.46	-0.20	1.75
3	0.26	0.34	0.24	0.09	0.05	2.73	3.34	3.07	0.94	0.39
Big	-0.22	0.30	0.29	0.22	0.60	-1.70	1.49	3.48	2.39	3.69
			m					t(m)		
Small	-0.07	-0.03	-0.10	0.11	-0.02	-1.07	-0.88	-3.27	2.03	-0.34
1	0.09	-0.05	0.03	-0.05	-0.11	1.85	-1.39	0.68	-0.95	-2.78
2	0.01	-0.02	0.01	-0.19	-0.03	0.32	-0.51	0.22	-3.86	-0.57
3	0.08	0.00	0.08	0.03	0.04	3.13	0.14	3.42	0.99	0.66
Big	-0.32	0.06	-0.03	0.18	-0.02	-5.76	0.48	-0.73	4.64	-0.45
			il					t(il)		
Small	-0.01	0.04	0.01	0.08	0.10	-0.08	0.58	0.21	0.91	1.01
1	0.07	0.00	-0.03	0.02	0.02	0.66	-0.04	-0.36	0.26	0.28
2	-0.13	-0.08	-0.02	-0.12	0.07	-1.59	-1.34	-0.26	-2.15	0.90
3	-0.05	-0.13	-0.02	0.02	-0.10	-0.97	-2.49	-0.34	0.49	-1.07
Big	-0.08	0.21	0.02	-0.01	-0.03	-1.01	1.35	0.32	-0.20	-0.36

Notes: This Table reports regressions estimates and their t-statistics for the seven-factor model. The LHS variables are the monthly excess returns on the 25 size-B/M portfolios. The RHS are market excess returns, $R_{M,t}$-R_{ft}, size factor (SMB), value factor (HML), MOM factor (WML), ILLIQ factor (ILML), OP factor (RMW), and INV factor (CMA).

However, the slopes are statistically negative for all the large stocks in all the models; this could be a sign of a reverse size effect for these large stocks. The SMB slope for the large-value portfolio (-1.53, t=-10.61)[11] is the lowest value among all the SMB slopes. The HML slopes for the value portfolios are statistically positive and higher than the slopes of the growth portfolios, which are negative, and some are significant. The HML slope for the large-value portfolio (0.95, t=5.40) is the highest slope in the HML slopes. This means that the value factor is a priced risk factor.

[11] t-statistics are calculated from standard errors that are robust to heteroskedasticity, using the method of White (1980).

The slopes of the CMA are negative in general; six slopes are statistically significant and negative. The INV slope for the large-value portfolio (0.17, t=0.97) is the second-highest slope. Hence, we can conclude that there is no clear INV effect in our sample. The RMW slopes are positive in general; nine slopes are statistically significant and positive, whereas three slopes are statistically significant and negative. The OP slope for the large-value portfolio (0.60, t=3.69) is the highest slope. Therefore, we find some evidence of OP effect in our sample. Moreover, the slopes of the WML factor, in general, are insignificant for most of the portfolios. The MOM slope for the large-value portfolio (-0.02, t=-0.45) is the second-highest slope among the value portfolios. Thus, the MOM effect seems unclear.

The ILLIQ slopes have just two significant values. This means that there might be no ILLIQ effect in our sample. This may be caused by the fact that the portfolios that we used to construct the ILML factor are not well-diversified portfolios, given the small number of stocks that are frequently traded. Regarding the large-value portfolio, the factors' slopes suggest that this portfolio is dominated by large stocks whose returns behave like those of profitable, aggressive, illiquid firms that grow slowly.

In relation to the other models, we observe that the number of portfolios exhibiting significant intercepts generally decrease as we add more factors. The multifactor models' slopes show similar results to those of the seven-factor model mentioned above.

The market, SMB, HML, and RMW factors in the models that include them are found to be relevant in the MENA region. Although our results do not show clear evidence of the ILLIQ effect, when we analyse the portfolios formed based on the size-ILLIQ sort, we find a positive and significant ILML slope for the extreme small-illiquid portfolio.

5.4. Discussion

In a nutshell, we can conclude that there is evidence for a standard size effect for small size portfolios and a reverse size effect for large size portfolios for this region, based on the regressions details for the size-B/M sort portfolios (and other size sort sets). There is also evidence of a value effect since most of the HML slopes are significantly positive for the value stocks in all the models, which indicates that the value portfolios have higher returns than the growth portfolios. Moreover, we can say there is also some evidence of a profitability effect, since most of the slopes are positive and significant. However, there is no clear evidence supporting momentum, illiquidity and investment effects in the MENA region.

Our results regarding the size and value are consistent with Van der Hart et al. (2003), who find that both size and value are relevant risk factors in all the emerging markets that they studied. Regarding illiquidity, our results are consistent with Rouwenhorst (1999), who finds that contrary to his expectations, the illiquidity factor is not a priced factor in the emerging markets that he studies. However, the fact that the portfolios that we used to construct this factor are not well-diversified portfolios, given the small number of stocks that are frequently traded, may have some impact on the results for this factor. Regarding investment, our finding is consistent with some studies such as Fama and French (2017), who find that this factor is not present in the European and Asia Pacific markets. Regarding momentum, our results are consistent with Cakici, Fabozzi, and Tan (2013), who find that there is no momentum effect in the Eastern Europe emerging market. One possible explanation for the absence of this effect may be Chui, Titman, and Wei's (2010) argument that momentum returns are more robust in countries that value individualism. Most of the countries in our dataset are characterized by the low value of the individualism index. Rouibah, Khalil and Hassanien (2009) show that the average individualism index score of MENA markets is 40.5 and referred to them as collectivist cultures. Overall, our findings seem to be consistent with the conclusion that investment and momentum effects are stronger in developed markets than in emerging markets (Zhang, 2017).

In summary, although our results suggest that the seven-factor model is the best model to explain stock returns in the MENA markets, no factor seems to dominate on a regular basis. The short sample period and the fast-changing market conditions due to political and economic instability during the period, the fact that priced risk factors may be different during different sub-periods and the way the different factors are measured are some issues that may explain our findings.

6. Conclusions

The empirical evidence in the prior literature shows that there are numerous factors in addition to the market factor that help explain the pattern of asset returns. This paper investigates this issue by examining the return patterns of emerging and less developed stock markets. Despite the importance of the MENA stock markets, to the best of our knowledge, there are no studies that construct and analyse the explanatory power of different risk factors in this region. This study examines whether the factors found to be significant in explaining stock returns in both developed and other emerging markets are also significant for the MENA markets. We find a significant standard size effect in the small size portfolios and a reverse size effect in the large size portfolios in our sample. We also find a significant value effect and some evidence of a profitability effect. Moreover, we find no clear evidence of investment, momentum and illiquidity effects, although the illiquid portfolios present higher returns than the liquid ones, particularly for the small size portfolios. This finding is not consistent with the expectation that illiquidity should be a priced factor on emerging markets. However, the measure used for this factor may have some limitations.

Regarding the alternative asset pricing models, our results show that the market factor alone cannot explain the excess returns on the MENA stocks. The inclusion of size and value improves the explanatory power of the CAPM, but it is still significantly rejected. The inclusion of the profitability and the investment factors improves the three-factor model performance, but the model is still significantly rejected. Inclusion of the momentum and the illiquidity factors enhances the model's explanatory power, and the models that do so become more acceptable using the GRS test. The best model based on the intercepts analysis, the GRS test, the AIC analysis and the adjusted R^2 differences analysis is the seven-factor model in all size sorts.

This paper's findings have important implications for portfolio management and portfolio performance evaluation in the emerging markets as a whole and, specifically, in the MENA region. In addition, it has essential practical implications for many interested participants in this region, such as national investors, international investors and policy makers. Our findings provide evidence on additional important factors that must be considered when investors in the emerging financial markets want to diversify away the risk or achieve higher excess return. For the purpose of portfolio performance evaluation in the MENA markets our results show that the seven-factor model is the model that should be used.

It is relevant to mention here what we consider to be possible limitations of the study. First, the study period is relatively short. Second, from the 21 countries that compose the MENA region, we were able to obtain data for only 13 countries. Unfortunately, not all countries are included in the DataStream database, such as Yemen, and some countries do not have any available information such as Syria. Third, the analysis of different markets with different levels of development may affect the reliability of the data that we obtained. Fourth, the study period is mainly a crisis period, which may affect our results. Some of these limitations may be addressed in future research.

For further research, it would be of interest to analyse whether the models' performances change in different sub-periods and whether different factor measurements have an effect on the performances of the models.

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