Full text document (pdf)

Citation for published version

Abadi, R., & **Silva, F.** (2019). Do Fundamental Portfolios Outperform in the MENA Equity Markets? *International Journal of Islamic and Middle Eastern Finance and Management*, 12(2), 265-281.

DOI

<https://doi.org/10.1108/IMEFM-07-2018-0230>

Link to record in RepositóriUM

<https://repositorium.sdum.uminho.pt>

Document Version

Author's Accepted Manuscript

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Do Fundamental Portfolios Outperform in the MENA Equity Markets?

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Acknowledgments

This work was carried out within the funding with COMPETE reference no POCI-01-0145-FEDER- 006683, with the FCT/MEC's (Fundação para a Ciência e a Tecnologia, I.P.) financial support through national funding and by the ERDF through the Operational Programme on "Competitiveness and Internationalization COMPETE 2020 under the PT2020 Partnership Agreement".

Do Fundamental Portfolios Outperform in the MENA Equity Markets?

Abstract

Purpose - This study investigates the performance of fundamental weighted portfolios (using sales, cash flow, dividend, book value and a composite of all these variables), an equal weighted portfolio and a smoothed cap-weighted portfolio in the Middle East and North Africa (MENA) markets. The performance of these portfolios is compared with that of a cap-weighted portfolio for the period 2005 to 2015.

Methodology - The portfolios are formed using different concentration levels, different construction schemes and different sub-regions. The performance is assessed using a large set of risk-adjusted performance measures including more robust measures in the context of multi-factor models, such as the Fama and French (1993) three-factor model, the Fama and French (2015) five-factor model and a seven-factor model.

Findings - The results show that the fundamental portfolios, with the exception of the sales portfolio, underperform the cap-weighted portfolio using either traditional or more robust risk-adjusted performance measures. The underperformance of the fundamental portfolios is found to be robust using different concentration levels, different construction schemes and different sub-regions. The results also show that the equal weighted portfolio outperforms the cap-weighted portfolio using traditional risk-adjusted measures. However, after controlling for additional risk factors this outperformance disappears.

Originality - The results of the study add evidence to the debatable propositions on the performance of fundamental portfolios in emerging markets. The failure of fundamental indexation in the emerging markets could help the researchers and the academics to search for the best weighting method that could be used as an alternative to the cap-weighted indexation method. Furthermore, the findings may help domestic and international investors, practitioners and decision-makers to deepen their knowledge in terms of the best portfolio's construction scheme in the MENA region.

Keywords Fundamental weighted portfolios, cap-weighted portfolios, equal weighted portfolios, smoothed cap-weighted portfolios, MENA markets.

Paper type Research paper

1. Introduction

To measure the performance of a stock market, a market index is usually used. “An index is a group of securities chosen to represent an unbiased view of the risk-and-reward attributes of a market or a portion of a market” (Philips, Kinniry, Walker and Thomas, 2011, p.14).

The most used index construction method is the market capitalization; which is a method that weighs each constituent according to its price multiplied by its common outstanding shares. This method favours the companies with anticipated future success and rewards this success today. There are many major indices that are constructed based on this method, such as the DAX (Frankfurt), the S&P 500 (New York), and the MSCI UK (London). However, some studies have found that the weights based on market capitalization in equity index construction suffer from tough criticisms. Haugen and Baker (1991) and Grinold (1992) provide empirical evidence that there is no efficient risk-return trade-off in market cap-weighted (CW) indices. Nevertheless, the CW method is still widely used since it is a passive strategy that needs no/or limited management fees, requires low trading costs and no rebalancing costs. Moreover, this method assigns substantial weights to the largest companies, which are the most heavily traded stocks, thus reducing expected portfolio transaction costs (Hsu, 2006; Arnott, Hsu and Moore, 2005).

Therefore, important questions arise for academics and researchers: Is the market CW portfolio providing the optimal risk-return relation to investors? And are there alternative ways to build an index? One proposed answer is fundamental weighted (FW) indices that allocate weights on the basis of accounting data. The idea of using the accounting information for equity selection and evaluation is not a new idea. Some researchers provide evidence that investment strategies based on the prediction of the future changes in some accounting data achieve abnormal returns (Ou and Penman, 1989; Holthausen and Larcker, 1992). Further, the accounting information of companies is used in asset valuation by financial analysts and market indices providers. The FW indices have been suggested by Treynor (2005), Arnott *et al.* (2005) and Hsu (2006). Arnott *et al.* (2005) find that the FW indices (using book values (BV), cash flows (CF), dividends (DIV) and sales) outperform the traditional ones since these fundamental variables are not affected by the mispricing of irrational investors. They argue that the superior returns of these indices roots from the fact that CW indices over-weight the over-valued stocks and under-weight the under-valued stocks.

Motivated by the potential weaknesses and criticisms associated with CW indices, we investigate the risk-adjusted performance of FW portfolios based on accounting data (using sales, CF, DIV, BV and a composite of all these variables) compared to that of a CW portfolio

in the MENA equity markets over the period 2005 to 2015. Further, we analyse the risk-adjusted performance of a smoothed cap-weighted (SCW) portfolio that uses smoothed share prices and may be an alternative to the FW portfolios as proposed by Chen, Chen and Bassett (2007) and an equal weighted (EW) portfolio that minimize the concentration risk that characterizes the CW approach.

We conduct our study in the MENA region because the stock markets in this region are generally small, relatively illiquid, and lack transparency. Thus, stock markets in this region can be classified as less efficient markets with a high proportion of small companies, since they are emerging markets (Harrison and Moore, 2012). The prices of the traded shares in stock exchanges could deviate substantially from their fair value, and so CW indices could create a return drag and FW indices would be a better alternative (Hsu and Campollo, 2006). The majority of previous studies regarding FW indices have been conducted mainly in the US and European markets, and no study to the best of our knowledge has been conducted in the MENA region. Hence, the aim of this research is to construct a CW portfolio using the traditional methodology [1], FW portfolios using Arnott *et al.*'s (2005) methodology, a SCW portfolio using Chen *et al.*'s (2007) methodology and an EW portfolio. The performance of the CW portfolio is compared with all those constructed portfolios. Therefore, the contributions of this study are threefold. First, it is the first study that analyses and compares the performance of FW portfolios to that of a CW portfolio in the MENA region. Second, it also contributes by using more robust risk-adjusted performance measures in the context of multi-factor models, namely the Fama and French (2015) five-factor model and a seven-factor model that includes momentum and illiquidity factors (Abadi and Silva, 2017). Third, this study contributes to the literature by using different weighting schemes, different concentration levels and different sub-regions to analyse the performance of the constructed portfolios. We focus on two sub-regions: Gulf Cooperation Council Countries (GCC) that includes all the Gulf countries that are politically stable (Bahrain, Oman, Qatar, Kuwait, Saudi Arabia and the United Arab Emirates) and Countries in Transition (CT) that includes countries which are politically unstable (Egypt, Israel, Jordan, Lebanon, Morocco, Palestine and Tunisia).

The structure of this paper is as follows. In section 2 we cover the literature review related to the different methods to construct equity indices and portfolios. Section 3 describes the methods for portfolios construction and the risk-adjusted performance measures. In section 4 we present the dataset. Section 5 presents and discusses the empirical results. In section 6 we present the main conclusions.

2. Literature Review

CW indices are widely used and seen as the generally accepted benchmark for investment performance measurement. CW indices consider risk and expected growth by using the market prices of stocks as proxies for their unobservable intrinsic values. If market prices have noise, CW indices performance may not be accurate. From this observation, the fundamental weighting scheme brings a new way of weighting, which depends on accounting variables rather than market prices. In this field, there are several studies that have been conducted to analyse the different types of indexation methods.

Chow, Hsu, Kalesnik and Little (2011) classify the alternative equity indices into heuristics-based (equal weighting, diversity weighting, risk-clusters equal weighting and fundamental weighting), and optimization based (minimum-variance portfolio, maximum diversification, and risk-efficient indexation). They find that these alternative indices have higher volatility and higher returns than the S&P 500 as a benchmark. Furthermore, they find that the fundamental index presents the highest Sharpe ratio, the highest alpha and the highest information ratio among the four heuristics-based alternative indices. The idea of fundamental indices is introduced by Arnott *et al.* (2005) who argue that CW indices over-weight stocks that are over-priced, and under-weight stocks that are under-priced, which cause a return drag. Arnott *et al.* (2005) find that FW indices outperform CW indices in the US equity market. This finding means that these fundamental indices maintain liquidity and investment capacity benefits of traditional CW indices. Arnott and West (2006) conduct their research on large and small US stocks, sector funds and international stocks. Their findings show that the excess returns of fundamental indices are considerably larger in the smaller companies and international portfolios. Hemminki and Puttonen (2008) show that the findings of the fundamental indexation in the European market are consistent with those of Arnott *et al.* (2005). These findings suggest that it is possible to produce consistently higher returns and higher risk-adjusted returns by reweighting a market CW index using fundamental values. Arnott, Hsu, Li, and Shepherd (2010) analyse fundamental indices on the debt market in the US and emerging markets. They find that the fundamental indices outperform the CW bond indices. Estrada (2008) analyses the effects of the fundamental indexation based on the dividends measure on international portfolios. He finds that the constructed index outperforms the market CW index by 1.90% per year. Stotz, Wanzenried, and Döhnert (2010) examine whether the return differences between the FW and the CW portfolios composed by stocks of the DJ Stoxx 600 index are driven by risk. They find that risk-adjusted returns are higher for the FW indices. Fisher, Shah and Timan (2015) state that fundamental indices are relatively passive portfolios with low turnover, low

tracking error and superior returns in comparison with CW indices. These superior returns of fundamental indices arise as a result of over-weighting the over-priced stocks by the CW index and under-weighting the under-priced stocks. More recently, Balatti, Brooks and Kappou (2017) in the UK equity markets, confirm that the FW portfolios outperform the CW portfolio. Conversely, Miziolek and Zaremba (2017) find that FW portfolios generate similar risk-adjusted returns to those of the CW portfolio. They conduct their study in Poland, Russia, and Turkey as the three largest European emerging markets.

However, most of the previously mentioned studies have not addressed the robustness of their findings and analyse the performance using the capital asset pricing model (CAPM) as the benchmark. Their approaches do not consider empirical studies, which show that CAPM is not an appropriate model for describing stock returns. Therefore, several studies have been conducted using the Fama and French (1993) three-factor and the Carhart (1997) four-factor models. Jun and Malkiel (2008) assess the performance of the FTSE RAFI US 1000 and show that this index exhibits a significant value tilt, and its alpha is not statistically different from zero. Houwer and Plantinga (2009) find that fundamental portfolios generate statistically significant positive alphas and have significant factor loadings on the size and value risk factors. In contrast, Hsu, Kalesnik, and Surti (2010) find that, on average, FW indices alphas are negative and statistically significant. Walkshausl and Lobe (2010) find that fundamental indices outperform the CW index in a global context, even after controlling for the value premium within the Carhart (1997) four-factor model, but the same is not observed for country-specific indices. Basu and Forbes (2014) find that the outperformance of FW portfolios in the Australian market is much higher than in any other equity market. Furthermore, they argue that this outperformance is not attributed to size, value or momentum risk factors. In relation to emerging markets, Hsieh (2013) finds that fundamental indices have significant exposures to the size and value risk factors. He argues that the inherent value bias or avoidance of large caps is the source of fundamental indices outperformance. Chow *et al.* (2011) adjust all the investment strategies that they analyse for the market, size, value, and momentum factor loadings. They find that only the global fundamental indexation strategy displays a statistically significant positive alpha.

Using different levels of concentration (top 200, 100, 50 and 30 stocks), Hsieh, Hodnett and Rensburg (2012) construct fundamental indices based on the large established firms in the global equity market and compared these indices to market CW indices for the period 1991-2008. They find that the FW indices outperform CW indices over the overall examination period and in two sub-periods. Hsieh *et al.* (2012) mention that FW indices are mean-variance

efficient proxies for the evaluation of large firms' performance. Their findings reveal that the level of portfolio concentration hardly affects the performance of FW indices, due to the fact that removing the price element from the weighting of fundamental indices mitigates the small firm anomaly. Further, they also find that the CW index is affected by firm size while the fundamental indices are not, since these indices are constructed from price insensitive attributes.

On an alternative approach, Chen *et al.* (2007) use a smoothed average of standard cap-weights instead of using accounting data, based on the assumption that market prices are unbiased but noisy approximations for fundamentals. They find that SCW portfolios outperform CW portfolios in the US market approximately by 1% a year. Fongwa (2015) examines the performance of FW portfolios (sales, BV, earnings, DIV and SCW) with different concentration levels (top 50 and mid-100 stocks) against a CW reference portfolio. His results show that most FW portfolios are more mean-variance efficient than the CW reference portfolio. More specifically, he finds that the SCW portfolio underperforms the other FW portfolios but it outperforms the CW portfolio.

Stotz et al. (2010) argue that the fundamental metrics can also be criticized, even though irrational investors have limited impacts on these indices compared to the CW indices. The book value may produce different stock weights according to the accounting practice that companies use. The sales could be very different across industries based on the nature of their operations. Moreover, a company that uses dividends to buy back its shares or to finance its investments will have zero weight in a dividend index and thus the dividends fundamental index can also be criticized. Perold (2007) also criticises the fundamental indexing strategy and states that FW indices are value tilt strategies. He argues that, in general, value stocks produce higher returns than any index since these higher returns exist either because the value stocks are riskier or because they are mispriced. Asness (2006) argues that FW portfolios may outperform in some periods and underperform in other periods since he finds that the cap-weighted indices outperform the FW indices for the period from 1999-2000.

In summary, the previous empirical studies have documented contradictory and debatable results regarding the performance of FW indices in comparison with CW indices. Moreover, most of the studies have not addressed the robustness of their findings, using alternative performance measures. In particular, it is important to investigate the performance of these alternative indices using more robust risk-adjusted performance measures in the context of recently developed multi-factor models.

3. Methods

3.1. Portfolios construction methods

The methods used to construct the FW portfolios and the SCW portfolio are based on Arnott *et al.* (2005) and Chen *et al.* (2007), respectively. As fundamental metrics, we use BV, CF, DIV, sales and a composite of these fundamental metrics (COMP). We first construct portfolios using 100% of the underlying stocks in our dataset. To test if portfolio's concentration level has an effect on portfolio performance, we rank stocks by their market capitalization and construct portfolios using the largest 100 (50) stocks, and independently using the smallest 100 (50) stocks. We also investigate the effect of construction scheme on the portfolio performance, by constructing portfolios including the largest 100 stocks and the smallest 100 stocks in two ways: first, we use the CW portfolio constituents and reweight them based on the fundamental variables, second, we independently rank and weight stocks according to each fundamental variable.

In an EW portfolio, the weight is the same to each stock in a portfolio and is denoted by:

$$X_t^{EW} = 1/N_t, \quad (1)$$

where N_t is the number of stocks in the portfolio at time t .

The weight of a stock i in a market CW portfolio is the market value of the firm divided by the market value of all companies in the portfolio and is denoted by:

$$X_{i,t}^{MV} = MV_{i,t} / \sum_{j=1}^N MV_{j,t}, \quad (2)$$

where $MV_{i,t}$ is the market value of company i at time t , and N is the number of stocks in the portfolio.

The weight of a stock i in a SCW portfolio is obtained using the median weight for the past 12 months.

The weight of each stock for each fundamental metric is defined as:

$$X_{i,t}^{FW} = F_{i,t-1} / \sum_{j=1}^N F_{j,t-1}, \quad (3)$$

where $F_{i,t-1}$ is the fundamental metric (for example, sales) of company i at fiscal year-end $t-1$ closest to t ($t-1 < t$). Note that $F_{i,t-1}$ is the fundamental value of the total company and not value on a per-share basis.

The weight considering the composite of fundamental metrics, is calculated as:

$$X_{i,t}^{COMP} = 1/4 \times (X_{i,t}^{BV} + X_{i,t}^{CF} + X_{i,t}^{DIV} + X_{i,t}^{Sales}) \quad (4)$$

Finally, returns on the portfolios are calculated as:

$$R_{t+1}^{Index} = \sum_{i=1}^N X_{i,t} \times R_{i,t+1}, \quad (5)$$

where $R_{i,t+1}$ is the stock's return in $t+1$.

The portfolios are rebalanced annually on 31 December. The month of December has been chosen because of the simplicity to compare companies at the end of the year.

The portfolio turnover in year t is calculated as:

$$Turnover_{p,t} = \sum_{i=1}^N |\Delta W_{i,t}|, \quad (6)$$

where:

$$\Delta W_{i,t} = W_{i,t} - (W_{i,t-1} \times (1 + R_{i,t}) / (1 + R_{p,t})), \quad (7)$$

N is the total number of securities in the portfolio, $W_{i,t}$ is security i weight in portfolio p in year t , $W_{i,t-1}$ is security i weight in portfolio p at the end of the previous year, $R_{i,t}$ is security i return in year t and $R_{p,t}$ is portfolio p return in year t .

3.2. Risk-adjusted performance measures

This section presents the risk-adjusted measures that are used to analyse the performance of the constructed portfolios. Portfolio performance is assessed using several risk-adjusted measures: traditional measures including the Jensen's alpha, the Treynor ratio, the Sharpe ratio, and the information ratio, the Sortino ratio, which is a downside risk-adjusted measure, and a set of more robust risk-adjusted performance measures based on the Fama and French (1993) three-factor model, the Fama and French (2015) five-factor model and a seven-factor model.

The Jensen's (1968) alpha (the regression intercept a_p) is estimated using the CAPM times-series regression, as expressed in the following Equation:

$$R_{p,t} - R_{f,t} = a + b(R_{M,t} - R_{f,t}) + \varepsilon_t, \quad (8)$$

where $R_{p,t}$ is the return on the portfolio p in month t , $R_{f,t}$ is the risk-free rate, b is portfolio p beta coefficient, $R_{M,t}$ is the return of the market CW portfolio in month t and ε_t is the regression residual in month t .

The beta coefficient (b) for the portfolio p is used to compute the Treynor (1965) ratio as follows:

$$\text{Treynor ratio}_p = (R_p - R_f) / b_p, \quad (9)$$

where R_p is portfolio p average returns during the estimation period and R_f is the average of the risk-free rate during the estimation period.

The Sharpe (1966) ratio of portfolio p is calculated as:

$$\text{Sharpe ratio}_p = (R_p - R_f) / \sigma_p, \quad (10)$$

where σ_p is the standard deviation of returns on the portfolio p during the estimation period.

The Sortino and Price (1994) measure, usually known as the Sortino ratio, is computed as:

$$\text{Sortino ratio}_p = (R_p - R_f) / \sigma_{s-d,p} \quad (11)$$

where $\sigma_{s-d,p}$ is the semi deviation of portfolio p 's returns, computed using only the negative returns.

To test the statistical significance of the Sharpe ratio and Sortino ratio differences, the Jobson and Korkie (1981) test with the Memmel (2003) correction is used. The Z statistic approximately follows a standard normal distribution, and it is calculated as:

$$z = \frac{SR_1 SR_2}{\sqrt{1/T[2(1-\rho_{1,2}) + 1/2(SR_1^2 SR_2^2 - SR_1 SR_2(1+\rho_{1,2}^2))]} \quad (12)$$

SR_i is the portfolio's Sharpe ratio (Sortino ratio), T is the number of observations and $\rho_{1,2}$ is the correlation between portfolios 1 and 2.

The information ratio of portfolio p is calculated as in Goodwin (1998):

$$\text{Information ratio}_p = E(R_{p,t} - R_{M,t}) / \sigma(R_{p,t} - R_{M,t}), \quad (13)$$

where $E(R_{p,t} - R_{M,t})$ is the average excess return of the portfolio p over the market CW portfolio and $\sigma(R_{p,t} - R_{M,t})$ is the standard deviation of the excess return.

The Fama and French (1993) model, the Fama and French (2015) model and a seven-factor model are also used to analyse portfolio performance. These models are estimated from the following Equations:

$$R_{p,t} - R_{f,t} = a + b(R_{M,t} - R_{f,t}) + s(SMB) + h(HML) + \varepsilon_t \quad (14)$$

$$R_{p,t} - R_{f,t} = a + b(R_{M,t} - R_{f,t}) + s(SMB) + h(HML) + r(RMW) + c(CMA) + \varepsilon_t \quad (15)$$

$$R_{p,t} - R_{f,t} = a + b(R_{M,t} - R_{f,t}) + s(SMB) + h(HML) + r(RMW) + c(CMA) + il(ILML) + m(WML) + \varepsilon_t \quad (16)$$

The left hand side (LHS) variable ($R_{p,t} - R_{f,t}$) is the monthly average excess returns of the constructed portfolios. The $R_{M,t}$ is the return of the market CW portfolio in month t . SMB , HML , RMW , CMA , WML and $ILML$ are the size (that captures the excess return of small stocks over big stocks), value (that captures the excess return of value stocks over growth stocks), profitability (that captures the excess return of high profitability stocks over low profitability stocks), investment (that captures the excess return of conservative stocks over aggressive stocks), momentum (that captures the excess return of prior year winner stocks over loser stocks) and illiquidity (that captures the excess return of illiquid stocks over liquid stocks) factors, respectively. These factors for the MENA region are computed by the researchers.

4. Data

Monthly total return data are obtained from Thomson Reuters DataStream database for all firms listed on all exchanges of 13 countries in MENA region, which covers, Bahrain, Egypt, Jordan, Israel, Kuwait, Lebanon, Morocco, Oman, Palestine, Qatar, Saudi Arabia, Tunisia and the United Arab Emirates. The MENA region also includes other markets, but firms of these countries do not have available data in the DataStream. Therefore, our

final dataset includes the markets of 13 countries from December 2004 to December 2015. The period is selected to have historical data as long as possible and to have coverage of broad markets. To avoid survivorship bias, delisted stocks are included until they disappear. It is relevant to mention that 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 available at least for one of the following variables: Sales, BV, CF and DIV. These company-accounting items are obtained from the DataStream database complemented with hand-collected raw data from the companies' financial reports, in order to minimize missing data and to ensure that the dataset is large enough. The one-month US Treasury bill rate is used as the proxy for risk-free rate and it is downloaded from Professor Kenneth French website.

For the fundamental variables, we follow Arnott *et al.* (2005), except we use three-year average for sales, CF and DIV rather than five years because the time period is not long enough. If a fundamental metric is negative, it is set equal to zero. This approach excludes short positions in stocks. However, it may introduce a potential bias into our data, given that companies with negative metrics are replaced with zero in the dataset. In our dataset the number of firms with negative fundamentals is rather small. In addition, we consider several fundamentals, as well as a combination of them; therefore, excluding firms with negative fundamentals do not cause a significant problem for our analysis. Moreover, for those companies that do not pay DIV we exclude this metric and use the average of the three other metrics to calculate the composite fundamental metric of such stocks.

In terms of the sectorial composition, the final dataset includes 35% financial, 2% utility, 2% transportation, 4% oil and 57% industrial stocks. The weights of the different sectors for all the constructed portfolios are also explored to examine the changes in sector allocation from one portfolio to another over time. Figure 1 shows the sectorial allocation in the COMP and the CW portfolios over the sample period. For these two portfolios the sector allocation is not substantially different. The COMP portfolio exhibit a slightly higher allocation in oil stocks and it also shows a slightly less stable allocation to the financial sector than the CW portfolio. The weight of the financial sector in the COMP portfolio shows a higher decrease in 2006 and then increases over time, particularly, during the period 2007-2009. In relation to the other portfolios, although not reported, we observe that the sales portfolio exhibits the lowest allocation to the financial sector.

Further, the sales and the CW portfolios are characterized by the most stable sectorial allocation over time, particularly in what regards the financial sector.

Insert Fig 1 here

5. Empirical Results and Analysis

5.1. Analysis of portfolio performance using all stocks universe

Table 1 shows the risk and returns attributes for all the constructed portfolios using all the stocks in our dataset. Panel A of Table 1 reports the ending value of \$1 investment at the beginning of the period, mean annualized returns, annualized standard deviation [2], beta, turnover ratio and several risk-adjusted performance measures namely the Sharpe ratio, Sortino ratio, Treynor ratio, information ratio and Jensen's alpha. Comparing the results of the CW portfolio with those of the accounting based FW portfolios we find that the highest ending value for a \$1 investment at the beginning of the period and the highest average annual returns is for the CW portfolio with \$6.44 and 18.45%, respectively. The BV portfolio generates the lowest ending value for a \$1 investment and the lowest average annual returns with \$3.29 and 11.43%, respectively. All the FW portfolios generate lower returns compared with the CW reference portfolio. The return generated by the reference CW portfolio is on average 5.83 (18.45%-12.62%) percentage points higher than that of the composite FW portfolio. The return differences between the CW portfolio and the FW portfolios are statistically significant for all portfolios, with the exception of the sales portfolio. The reference CW portfolio presents the highest volatility with a value of 19.00%, while the sales portfolio presents the lowest volatility with a value of 18.56%. The betas for all the FW portfolios are slightly lower than one. In terms of the portfolio's turnover, the CW portfolio has the highest turnover ratio, while the sales portfolio has the lowest ratio [3]. Lower FW portfolios' turnover is a result of using a three-year average for the accounting variables. In relation to risk-adjusted performance measures, the CW portfolio presents the highest Sharpe ratio and Sortino ratio with values of 0.33 and 0.32, respectively. All the FW portfolios present lower Sharpe ratios and lower Sortino ratios in comparison with the CW portfolio, with the differences being statistically significant except for the sales portfolio. Also, all the FW portfolios have lower Treynor ratios than that of the CW portfolio. The information ratios of all the FW portfolios are negative, indicating that the portfolios are unable to produce excess returns relative to the reference

CW portfolio. The Jensen's alpha is also negative and statistically significant, except for the sales portfolio that has an insignificant alpha.

Further, the CW portfolio is also compared to an EW portfolio and a SCW portfolio. The results show that although the EW portfolio has lower annual returns than the CW portfolio, the difference is not statistically significant. The EW portfolio also has a lower volatility than the CW and a lower beta. Moreover, it has a significantly higher Sharpe ratio, significantly higher Sortino ratio, higher Treynor ratio, and a positive and statistically significant alpha, although only at the 10% level. On the contrary, and similarly to the FW portfolios, the SCW portfolio tends to underperform. Therefore, based on these measures, we find some evidence for the outperformance of the EW portfolio among all the constructed portfolios.

The performance of the constructed portfolios is also analysed using more robust risk-adjusted measures based on the Fama and French (1993) three-factor model, the Fama and French (2015) five-factor model and a seven-factor model [4]. Table 1, Panel B reports the alphas of these models for all the constructed portfolios. The coefficients of the different risk factors of the seven-factor model are also reported.

Insert Table 1 here

The alphas are negative and statistically significant for all the constructed portfolios, with the exception of the EW portfolio. The EW portfolio's alpha becomes negative but insignificant after controlling for additional risk factors, which means that its outperformance based on the traditional risk-adjusted measures and Sortino ratio disappears. Analysing the coefficients of the risk factors, we observe that, in general, the market betas are slightly higher than one for most portfolios. The coefficient of the size factor (coefficient s) is positive and statistically significant for all portfolios except the BV and the SCW portfolios. The EW portfolio has the highest exposure to the size premium with a value of 0.67 and the BV portfolio has the lowest exposure with a value of -0.04. The loadings on the value factor (coefficient h) are statistically significant only for the BV portfolio. This finding indicates that this portfolio has a higher exposure to value stocks returns. The coefficient of the investment factor (coefficient c) is negative and statistically significant at the 5% level just for the BV portfolio. This suggests that this portfolio is more exposed to aggressive stocks. The loadings on the profitability factor

(coefficient r) are negative and significant for the DIV and the SCW portfolios, which means that these portfolios are more exposed to stocks with low profitability. The coefficient of the illiquidity factor (coefficient il) is negative and statistically significant at the 10% level just for the sales portfolio. Finally, the loadings on the momentum factor (coefficient m) are positive and statistically significant for the sales, COMP and EW portfolios at the 10% level and at the 5% level for the SCW portfolio. Overall, it can be noted that, when additional risk factors are considered, abnormal returns are more negative than when the CAPM is used for all portfolios. Overall, the results of the multi-factor models confirm the superiority of the traditional CW portfolio. This finding is consistent with Walkshausl and Lobe (2010) who find that the abnormal returns of the fundamental portfolios are driven by the risk factors loadings and do not outperform the CW portfolio in emerging markets.

5.2. Analysis of portfolio performance using different concentration levels

To examine if the level of concentration has any effect on the performance of the different portfolios, we use the top 100 stocks [5] based on the market capitalization to construct all the portfolios. In other words, we choose the biggest 100 stocks and construct the different portfolios.

Table 2 reports the risk and return attributes for the constructed portfolios using the top 100 stocks. The results show that although the FW portfolios tend to have higher annual returns than using all stocks universe, they also exhibit higher volatility. In terms of the traditional risk-adjusted performance, the results are similar to those reported in Table 1. The sales portfolio shows some evidence as the foremost among the FW portfolios and the EW portfolio is found to outperform the CW portfolio. The seven-factor model alphas show that the sales and the EW portfolios perform similarly to the CW portfolio [6].

Insert Table 2 here

5.3. Analysis of portfolio performance using different weighting schemes

To analyse the effect of the construction schemes on the portfolios' performance, the FW portfolios are constructed separately and independently from the reference CW portfolio. In other words, we do not just reweight the same constituents of the reference CW portfolio, whilst we independently choose the highest 100 stocks based on each

fundamental metric. The composition of these portfolios shows that financial stocks dominate these portfolios.

Table 3 presents a summary of the risk and return attributes of the constructed portfolios for the biggest 100 (Panel A) and the smallest 100 stocks (Panel B).

Table 3, Panel A, shows that using a different construction scheme for big stocks portfolios does not affect the previous findings. All the FW portfolios with the exception of the sales portfolio underperform the CW portfolio; the EW portfolio is the superior portfolio using the traditional risk-adjusted measures and Sortino ratio. However, using more robust risk-adjusted measures, the findings show that all portfolios, except the EW portfolio, generate statistically significant negative alphas. The EW portfolio's alpha becomes insignificant, which indicates that the EW outperformance is due to its loadings on the additional risk factors.

Table 3, Panel B shows the effect of the construction scheme on the smallest 100 stocks portfolios. All the portfolios, except the SCW portfolio, have annual returns that are not statistically different from those of the CW portfolio. These portfolios have higher volatility and higher beta than the CW portfolio. The EW, sales and CF portfolios seem to perform similarly to the CW portfolio, since these three portfolios generate Sharpe ratios and Sortino ratios that are not statistically significant different from the CW portfolio's ratios. Further, these three portfolios have the highest Treynor ratios and Jensen's alphas which are not statistically different from zero. However, when more robust risk-adjusted measures are used only the sales and the EW portfolios perform similarly to the CW portfolio.

Insert Table 3 here

5.4. Analysis of portfolio performance for sub-regions

To analyse the robustness of our results, we divide the dataset into two sub-regions based on the political stability of the countries included in each sub-region, the GCC sub-region that is more politically stable and the CT sub-region that is politically unstable.

Table 4 reports risk and return attributes for these two sub-regions portfolios, using all stocks in each sub-region [7]. Similar to the MENA region results, the FW portfolios in the two sub-regions generate lower returns, higher volatility, lower Sharpe ratios, lower Sortino ratios and lower Treynor ratios than the CW and the EW portfolios. In terms of the best FW portfolio, the sales portfolio is the best in the GCC sub-region and the CF

and BV portfolios are the best in the CT sub-region. Moreover, using the more robust risk-adjusted measures all the FW portfolios in the GCC sub-region, except the sales portfolio, generate significantly negative alphas. The sales portfolio generates negative but insignificant alphas, while the EW portfolio generates a significantly positive alpha at the 10% significance level. In the CT sub-region, the multi-factor models alphas are negative and statistically significant for all the FW portfolios, while they are not statistically significant for the EW and the SCW portfolios. In general, the CT sub-region portfolios not only present higher annual returns than those of GCC sub-region, they also present lower volatility. However, although, the CT sub-region portfolios exhibit Sharpe ratios and Sortino ratios that are statistically higher than those of the GCC sub-region, the multi-factor models alphas are not statistically different. This evidence suggests that the portfolios in the CT sub-region outperform those in the GCC sub-region using the Sharpe ratio and the Sortino ratio, but this outperformance disappears using the more robust risk-adjusted measures. These results are due to the market characteristics of the CT sub-region that includes Israel, a country that has one of the largest and the most stable financial markets in the MENA region during the crisis periods. In addition, the GCC sub-region portfolios include more financial and oil stocks that are sharply affected by the global financial crisis. Nevertheless, the results confirm the underperformance of the FW in the two sub-regions.

Insert table 4 here

6. Conclusions

This study examines the performance of FW portfolios that weights stocks based on accounting data, a SCW portfolio that uses smoothed share prices and may be an alternative to FW portfolios and an EW portfolio that minimize the concentration risk that characterizes the CW approach. The findings document underperformance of these FW portfolios in comparison with the CW portfolio in the MENA region. All the FW portfolios, except the sales portfolio, generate returns and risk-adjusted ratios that are significantly lower than the reference CW portfolio. The sales portfolio is the only fundamental portfolio that has mean excess returns, Sharpe ratio and Sortino ratio that are insignificantly different from those of the CW portfolio. This result may be due to the fact that the sales portfolio is the one including the lowest percentage of stocks from the financial sector. However, using more robust risk-adjusted measures based on multi-

factor models, all the FW portfolios generate statistically significant negative alphas. Therefore, the FW portfolios underperform the CW portfolio. Our study also documents that the SCW portfolio underperforms the CW portfolio, whilst the EW portfolio outperforms the CW portfolio using the traditional risk-adjusted measures. After controlling for additional risk factors the EW portfolio outperformance disappears.

All the previous results are robust to different construction concentration levels, different construction schemes and different sub-regions. Although the findings of portfolios that are constructed using the smallest stocks and different constituents in each portfolio show some evidence regarding the CF and the sales portfolios outperformance, this outperformance disappears when more robust risk-adjusted performance measures are used. Our findings are consistent with those of Walkshausl and Lobe's (2010) who find that FW portfolios underperform in emerging markets (Taiwan, Columbia, Morocco, and Venezuela).

Moreover, our results provide some evidence that the portfolios have exposure to the size, value, investment, profitability, momentum and illiquidity risk factors. This result confirms the prevailing view in the literature (Walkshausl and Lobe, 2010; Stotz *et al.*, 2010; Hsieh, 2013) that shows that in most cases the outperformance of fundamental portfolios is driven by the risk factors loadings.

Although the expectations were that FW portfolios would outperform in emerging markets, since these markets are less efficient and the prices in these markets are noisier, they are not confirmed in the MENA region. Thus, our findings suggest that the fundamental variables do not have more information about the fair values of the stocks than the stock's price. From another perspective, the underperformance of the FW portfolios in this region could also be to the overweight position in the financial sector, which represents 35% of our dataset and whose stock prices dropped sharply during the global financial crisis. Furthermore, the MENA region had been affected by the Arab Spring uprisings in 2011 and by the Oil shock in 2014, which also affect financial sector prices. In conclusion, our results show that the BV, CF, DIV, COMP and SCW portfolios are not appropriate investment alternatives to the standard CW portfolio in the MENA region, while the EW and the sales portfolios could be good alternatives. Specifically, this region has a unique characteristic such as unstable political and economic situation, which makes our results differ from those in some of the previous literature.

Overall, our results add evidence to the debatable propositions on the performance of the FW portfolios in emerging markets. Further, the findings may help the domestic and international investors, practitioners and decision-makers to deepen their knowledge in terms of the best portfolio's construction scheme in the MENA region. For further research, it would be of interest to study the performance of all heuristics-based and optimization based weighting portfolios to find the best alternative to the CW portfolio, if there is any, in the MENA region. It would be also of interest to investigate the effect of the Arab Spring on the performance of FW portfolios. Moreover, an interesting avenue for further research would be to study the investor sentiment that may influence portfolio management and its evaluation in this region.

Notes

1. There is a MSCI CW index for this region, but the constituents of this index are not freely available, so a similar portfolio is constructed in this research based on the dataset of stocks collected for all the markets in this region. Another reason for constructing a CW portfolio, as opposed to just utilizing the MSCI index, is to allow a more reasonable, equitable and practical comparison.
2. The average of arithmetic monthly returns is annualized by $(1+R)^{12}-1$. We annualize the monthly standard deviation by multiplying it by $\sqrt{12}$.
3. We considered transaction costs to be equal to zero for all portfolios.
4. The risk factors are available for the MENA region only for the period 2007-2015.
5. We also constructed portfolios based on the top 50 stocks. The results are almost the same, with FW portfolios underperforming the reference CW portfolio.
6. We also used the smallest 100 stocks to construct the CW portfolio. We find similar results to those of the biggest 100 stocks with the FW portfolios underperforming the CW portfolio.
7. Portfolios constructed using the biggest 100 and the biggest 50 stocks in each of the sub region were also analysed and the results were similar to those reported in Table 4.

References

- Abadi, R. & Silva, F. (2017). *Common risk factors in stock returns in the MENA region*. Working paper.
- Arnott, R. D., & West, J. M. (2006), "Fundamental indexes™: Current and future applications", *ETFs and Indexing*, Vol. 2006 No.1, pp. 111-121.
- Arnott, R. D., Hsu, J. C., Li, F., & Shepherd, S. D. (2010), "Valuation-indifferent weighting for bonds", *Journal of Portfolio Management*, Vol. 36 No. 3, pp. 117-130.
- Arnott, R. D., Hsu, J., & Moore, P. (2005), "Fundamental indexation", *Financial Analysts Journal*, Vol. 61 No. 2, pp. 83-99.
- Asness, C. (2006), "The value of fundamental indexing", *Institutional Investor*, Vol. 31 No. 8, pp. 66.
- Balatti, M., Brooks, C., & Kappou, K. (2017), "Fundamental indexation revisited: New evidence on alpha", *International Review of Financial Analysis*, Vol. 51, pp. 1-15.
- Basu, A. K., & Forbes, B. (2014), "Does fundamental indexation lead to better risk-adjusted returns? New evidence from Australian Securities Exchange", *Accounting & Finance*, Vol. 54 No. 3, pp. 699-728.
- Carhart, M. M. (1997), "On persistence in mutual fund performance", *The Journal of Finance*, Vol. 52 No. 1, pp. 57-82.
- Chen, C., Chen, R., & Bassett, G. W. (2007), "Fundamental indexation via smoothed cap weights", *Journal of Banking & Finance*, Vol. 31 No. 11, pp. 3486-3502.
- Chow, T., Hsu, J., Kalesnik, V., & Little, B. (2011), "A survey of alternative equity index strategies", *Financial Analysts Journal*, Vol. 67 No. 5, pp. 37-57.
- Estrada, J. (2008), "Fundamental indexation and international diversification", *The Journal of Portfolio Management*, Vol. 34 No. 3, pp. 93-109.
- Fama, E. F., & French, K. R. (1993), "Common risk factors in the returns on stocks and bonds", *Journal of Financial Economics*, Vol. 33 No. 1, pp. 3-56.
- Fama, E. F., & French, K. R. (2015), "A five-factor asset pricing model", *Journal of Financial Economics*, Vol. 116 No. 1, pp. 1-22.
- Fisher, G., Shah, R., & Titman, S. (2015), "Decomposing fundamental indexation", *The Journal of Index Investing*, Vol. 6 No. 3, pp. 10-19.
- Fongwa, E. C. (2015), "Fundamental indexation and mean reversion on the Taiwanese equity market", Unpublished Manuscript, University of the Western Cape, Republic of South Africa.
- Goodwin, T. H. (1998), "The information ratio", *Financial Analysts Journal*, Vol. 54 No. 4, pp. 34-43.
- Grinold, R. (1992), "Are benchmark portfolios efficient?", *The Journal of Portfolio Management*, Vol. 19 No. 1, pp. 34-40.
- Harrison, B., & Moore, W. (2012), "Stock market efficiency, non-linearity, thin trading and asymmetric information in MENA stock markets", *Economic Issues*, Vol. 17 No. 1, pp. 77-93.

- Haugen, R., & Baker, N. (1991), "The efficient market inefficiency of capitalization weighted stock portfolios", *The Journal of Portfolio Management*, Vol. 17 No. 3, pp. 35-40.
- Hemminki, J., & Puttonen, V. (2008), "Fundamental indexation in Europe", *Journal of Asset Management*, Vol. 8 No. 6, pp. 401-405.
- Holthausen, R. W., & Larcker, D. F. (1992), "The prediction of stock returns using financial statement information", *Journal of Accounting and Economics*, Vol.15 No. 3, pp. 373-411.
- Houwer, R. & Plantinga, A. (2009), "Fundamental indexing: an analysis of the returns, risks and costs of applying the strategy", *available at SSRN: <https://ssrn.com/abstract=1343879>*
- Hsieh, H. (2013), "Unlocking the secrets of fundamental indexes: size effect or value effect? Evidence from emerging stock markets", *Investment Management and Financial Innovations*, Vol. 10 No. 4, pp. 48-63.
- Hsieh, H. H., Hodnett, K., & van Rensburg, P. (2012), "Fundamental indexation for global equities: Does firm size matter?", *Journal of Applied Business Research*, Vol. 28 No. 1, pp. 105-114.
- Hsu, J. C. (2006), "Cap-weighted portfolios are sub-optimal portfolios", *Journal of Investment Management*, Vol. 4 No. 3, pp. 1-10.
- Hsu, J. C., & Campollo, C. (2006), "An examination of fundamental indexation", *New Frontiers in Index Investing Journal of Indexes*, Vol. 58, pp. 32-37.
- Hsu, J., Kalesnik, V., & Surti, H. (2010), "An Examination of traditional style indexes", *Journal of Index Investing*, Vol. 1 No. 2, pp. 14-23.
- Jensen, M. C. (1968), "The performance of mutual funds in the period 1945–1964", *The Journal of Finance*, Vol. 23 No.2, pp. 389-416.
- Jobson, J., & Korkie, B. (1981), "Performance hypothesis testing with the Sharpe and Treynor measures", *The Journal of Finance*, Vol. 36, pp. 889-908.
- Jun, D., & Malkiel, B. (2008), "New paradigms in stock market indexing", *European Financial Management*, Vol. 14 No. 1, pp. 118-126.
- Kaplan, P. (2008), "Why fundamental indexation might-or might not-work", *Financial Analysts Journal*, Vol. 64 No. 1, pp. 32-39.
- Lakonishok, J., Shleifer, A., & Vishny, R. (1994), "Contrarian investment, extrapolation, and risk", *The Journal of Finance*, Vol. 49 No. 5, pp. 1541-1578.
- Memmel, C. (2003), "Performance hypothesis testing with the Sharpe ratio", *Finance Letters*, Vol. 1, pp. 21-23.
- Miziolek, T., & Zaremba, A. (2017), "Fundamental indexation in European emerging markets", *Romanian Journal of Economic Forecasting*, Vol. 20 No. 1, pp. 23-37.
- Ou, J. A., & Penman, S. H. (1989), "Financial statement analysis and the prediction of stock returns", *Journal of Accounting and Economics*, Vol. 11, No. 4, pp. 295-329.
- Perold, A. F. (2007), "Fundamentally flawed indexing", *Financial Analysts Journal*, Vol. 63 No. 6, pp. 31-37.

Philips, C. B., Kinniry Jr, F. M., Walker, D. J., & Thomas, C. J. (2011), "A review of alternative approaches to equity indexing", Unpublished Manuscript, Vanguard Investment Counseling and Research Group, US, available at:
<https://personal.vanguard.com/pdf/s287.pdf>

Sharpe, W. F. (1966), "Mutual fund performance", *The Journal of Business*, Vol. 39 No. 1, pp. 119-138.

Sortino, F. A., & Price, L. N. (1994), "Performance measurement in a downside risk framework", *The Journal of Investing*, Vol. 3 No. 3, pp. 59-64.

Stotz, O., Wanzenried, G., & Döhnert, K. (2010), "Do fundamental indexes produce higher risk adjusted returns than market cap indexes? Evidence for European stock markets", *Financial Markets and Portfolio Management*, Vol. 24 No. 3, pp. 219-243.

Treynor, J. L. (1965), "How to rate mutual fund performance", *Harvard Business Review*, Vol. 43, pp. 63-75.

Treynor, J. (2005), "Why market-valuation-indifferent indexing works", *Financial Analysts Journal*, Vol. 61 No. 5, pp. 65-69.

Walkshäusl, C., & Lobe, S. (2010), "Fundamental indexing around the world", *Review of Financial Economics*, Vol. 19 No. 3, pp. 117-127.

Figure 1- Sectorial allocation in the COMP and the CW portfolios

Table 1- Risk and return characteristics of the CW vs. FW, EW and SCW portfolios, using all stocks universe

Panel A: Risk and Return Characteristics of the Constructed Portfolios (2005-2015)										
Portfolio	Ending Value of \$1	Annual Return (%)	Annual Volatility (%)	Beta	Turnover Ratio (%)	Sharpe Ratio (%)	Sortino Ratio (%)	Treynor Ratio (%)	Inf. Ratio (%)	Jensen's Alpha (%)
Sales	4.12	13.73	18.56	0.91	10.84	0.32	0.30	17.90	-0.21	-0.22
CF	3.91	13.20***	18.70	0.97	15.89	0.28***	0.27***	16.09	-0.52	-0.34***
BV	3.29	11.43***	18.60	0.96	15.97	0.27***	0.26***	14.16	-0.73	-0.46***
DIV	3.53	12.14***	18.77	0.96	20.61	0.26***	0.25***	14.55	-0.46	-0.41***
COMP	3.70	12.62***	18.64	0.95	12.35	0.29***	0.27***	15.61	-0.45	-0.36***
CW	6.44	18.45	19.00	-	21.90	0.33	0.32	21.45	-	-
EW	6.09	17.84	15.22	0.61	9.34	0.50***	0.49***	30.34	-0.03	0.48*
SCW	5.94	17.58	19.68	1.03	22.15	0.32***	0.31***	20.36	-0.23	-0.11***
Panel B: Multi-Factor Models Alphas and the Seven-Factor Model Coefficients (2007-2015)										
	Three Factor	Five Factor	Seven-Factor							
Portfolio	Alpha	Alpha	Alpha	<i>b</i>	<i>s</i>	<i>h</i>	<i>c</i>	<i>r</i>	<i>il</i>	<i>m</i>
Sales	-0.63***	-0.67***	-0.45**	1.17***	0.31**	0.02	-0.15	0.01	-0.08*	0.05*
CF	-0.41***	-0.44***	-0.42***	1.07***	0.09*	-0.02	-0.04	0.00	0.00	0.00
BV	-0.38***	-0.40***	-0.35***	0.98***	-0.04	0.07**	-0.10**	0.00	0.00	0.02
DIV	-0.49***	-0.56***	-0.47***	1.10***	0.12**	-0.03	-0.02	-0.09**	-0.03	0.02
COMP	-0.48***	-0.52***	-0.43***	1.08***	0.12**	0.01	-0.08	-0.02	-0.02	0.03*
EW	-0.27	-0.36	-0.03	1.08***	0.67**	-0.07	-0.08	0.11	-0.03	0.12*
SCW	-0.09***	-0.09***	-0.08***	1.02***	0.00	0.00	-0.01	-0.02*	0.00	0.01**

Note: *, ** and *** stand for statistical significance at 10%, 5%, and 1%, respectively.

Table 2- *Risk and return characteristics of the constructed portfolios based on the biggest 100 stocks using the same CW portfolio's constituents*

Portfolio	Ending Value of \$1	Annual Return (%)	Annual Volatility (%)	Beta	Turnover Ratio (%)	Sharpe Ratio (%)	Sortino Ratio (%)	Treynor Ratio (%)	Inf. Ratio (%)	Jensen's Alpha (%)	Three-Factor Alpha	Five-Factor Alpha	Seven-Factor Alpha
Sales	5.02	15.79	20.48	0.97	9.89	0.31	0.31	19.31	-0.12	-0.16	-0.35**	-0.38**	-0.27
CF	4.27	14.10***	20.24	0.99	13.21	0.26***	0.26***	17.01	-0.44	-0.31**	-0.29***	-0.32***	-0.34***
BV	3.65	12.49***	20.21	0.99	12.59	0.25***	0.25***	15.45	-0.45	-0.42***	-0.25***	-0.27***	-0.25***
DIV	4.01	13.47***	20.69	1.00	19.69	0.25***	0.24***	15.87	-0.38	-0.37**	-0.40***	-0.46***	-0.41***
COMP	4.21	13.96***	20.30	0.99	10.62	0.27***	0.27***	16.89	-0.37	-0.31**	-0.32***	-0.36***	-0.32***
CW	6.47	18.50	20.14	-	18.17	0.31	0.31	21.89	-	-	-	-	-
EW	7.13	19.56	18.16	0.87	4.79	0.37**	0.37**	25.16	0.06	0.24*	0.00	0.05	0.17
SCW	6.16	17.98*	20.20	1.00	22.92	0.29***	0.29***	21.19	-0.21	-0.04*	-0.04	-0.04*	-0.05**

Note: *, ** and *** stand for statistical significance at 10%, 5%, and 1%, respectively.

Table 3- Risk and return characteristics of the constructed portfolios based on the biggest 100 and the smallest 100 stocks using different constituents of those in the CW portfolio

Panel A: The Biggest 100 Stocks													
Portfolio	Ending Value of \$1	Annual Return (%)	Annual Volatility (%)	Beta	Turnover Ratio (%)	Sharpe Ratio (%)	Sortino Ratio (%)	Treynor Ratio (%)	Inf. Ratio (%)	Jensen's Alpha (%)	Three-Factor Alpha	Five-Factor Alpha	Seven-Factor Alpha
Sales	3.79	12.89*	19.97	0.91	9.55	0.27*	0.27*	17.50	-0.20	-0.29	-0.67***	-0.68***	-0.45*
CF	3.65	12.48***	19.88	0.97	13.10	0.25***	0.24***	16.45	-0.51	-0.40**	-0.44***	-0.47***	-0.45***
BV	3.09	10.80***	19.98	0.97	12.64	0.23***	0.24***	13.77	-0.57	-0.53**	-0.36***	-0.39***	-0.36***
DIV	3.37	11.67***	19.96	0.96	18.74	0.23***	0.23***	14.23	-0.42	-0.45**	-0.50***	-0.56***	-0.46***
COMP	3.39	11.75***	19.85	0.96	9.95	0.25***	0.25***	15.09	-0.41	-0.44*	-0.50***	-0.53***	-0.43***
CW	6.47	18.50	20.14	-	18.17	0.31	0.31	21.89	-	-	-	-	-
EW	7.13	19.56	18.16	0.87	4.79	0.37**	0.37**	25.16	0.06	0.24*	0.00	0.05	0.17
SCW	6.16	17.98*	20.20	1.00	22.29	0.29**	0.29**	21.19	-0.21	-0.04*	-0.04	-0.04*	-0.05**
Panel B: The Smallest 100 Stocks													
Sales	5.33	16.42	15.64	1.00	15.86	0.48	0.47	18.31	-0.09	0.06	-0.13	-0.15	-0.06
CF	5.22	16.22	14.80	1.00	23.02	0.51	0.49	16.71	-0.10	0.04	-0.16***	-0.16***	-0.13***
BV	4.11	13.72*	15.32	1.04	17.58	0.44***	0.43***	14.19	-0.35	-0.18**	-0.29***	-0.29***	-0.26***
DIV	4.22	14.00	15.47	1.04	21.28	0.42***	0.40***	13.13	-0.26	-0.16*	-0.26***	-0.28***	-0.21***
COMP	4.37	14.36	15.02	1.02	15.86	0.47***	0.46***	14.66	-0.25	-0.11	-0.24***	-0.24***	-0.18***
CW	4.91	15.56	14.43	-	23.74	0.52	0.50	15.75	-	-	-	-	-
EW	5.70	17.15	15.43	0.91	10.31	0.47	0.47	19.44	-0.07	0.21	-0.14	-0.20*	-0.13
SCW	3.93	13.25***	14.28	0.98	22.44	0.44***	0.44***	14.36	-0.50	-0.15***	-0.12***	-0.12***	-0.13***

Note: *, ** and *** stand for statistical significance at 10%, 5%, and 1%, respectively.

Table 4- Risk and return characteristics of the constructed portfolios in the two sub-regions

Panel A: GCC Sub-Region													
Portfolio	Ending Value of \$1	Annual Return (%)	Annual Volatility (%)	Beta	Turnover Ratio (%)	Sharpe Ratio (%)	Sortino Ratio (%)	Treynor Ratio (%)	Inf. Ratio (%)	Jensen's Alpha (%)	Three-Factor Alpha	Five-Factor Alpha	Seven-Factor Alpha
Sales	3.61	12.38***	22.75	1.02	10.99	0.22***	0.22***	15.31	-0.33	-0.35**	-0.22	-0.21	-0.19
CF	3.63	12.44***	22.16	0.99	15.46	0.22*	0.23**	15.82	-0.45	-0.32**	-0.31***	-0.32***	-0.32***
BV	2.96	10.38***	21.56	0.96	16.25	0.22***	0.22***	13.88	-0.59	-0.43***	-0.35***	-0.37***	-0.34***
DIV	3.18	11.09***	21.48	0.96	18.97	0.21***	0.21***	14.55	-0.58	-0.38***	-0.45***	-0.48***	-0.45***
COMP	3.33	11.57***	21.82	0.98	12.29	0.22***	0.22***	14.91	-0.63	-0.37***	-0.30***	-0.32***	-0.29***
CW	5.52	16.81	22.02	-	20.66	0.28	0.28	20.78	-	-	-	-	-
EW	4.35	14.31	15.68	0.66	9.70	0.37***	0.37***	23.06	-0.07	0.21	0.12	0.17	0.23*
SCW	5.29	16.36	22.75	1.03	20.45	0.27	0.27	20.36	-0.18	-0.07	-0.05*	-0.05*	-0.04*
Panel B: CT Sub-Region													
Sales	4.87	15.48	20.36	1.18	11.85	0.30***	0.31***	15.57	-0.25	-0.58***	-0.65***	-0.70***	-0.69***
CF	4.66	15.02***	17.51	1.08	17.45	0.34***	0.34***	14.87	-0.48	-0.48***	-0.43***	-0.46***	-0.47***
BV	4.22	13.98***	16.03	0.99	17.27	0.34***	0.35***	14.51	-0.52	-0.43***	-0.31***	-0.33***	-0.33***
DIV	4.53	14.72***	19.13	1.15	22.98	0.31***	0.31***	13.36	-0.32	-0.60***	-0.47***	-0.48***	-0.50***
COMP	4.56	14.80***	17.93	1.10	12.81	0.33***	0.33***	14.52	-0.44	-0.52***	-0.47***	-0.49***	-0.50***
CW	7.47	20.06	15.79	-	21.71	0.47	0.48	20.28	-	-	-	-	-
EW	8.61	21.62	19.59	0.92	9.50	0.40	0.41	24.47	-0.09	0.23	0.15	0.13	0.17
SCW	6.52	18.58	16.18	1.00	21.89	0.42***	0.43***	18.67	-0.13	-0.11	-0.07	-0.07	-0.10

Note: *, ** and *** stand for statistical significance at 10%, 5%, and 1%, respectively.