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Econometrics and Metaheuristic Optimization Approaches to International Portfolio Diversification

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Abstract

Using advanced techniques of econometrics and a metaheuristic optimization approach, this study attempts to evaluate the potential advantages of international portfolio diversification for East Asian international investors when investing in the Middle Eastern emerging markets. Overall, the results of both econometric and the metaheuristic optimization methods are supporting each other. Findings of this study highlight the potential role of the Middle Eastern equity markets in providing international portfolio diversification benefits for East Asian investors. It is also found that the long and the short-term efficient frontiers in any of the intra or inter-regionally diversified portfolios do not provide similar benefits.

Keywords:

International portfolio optimization, Multiple-function genetic algorithm, Integration, Investment horizon, Emerging markets.

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Introduction

The primary desire of portfolio managers is to increase the performance of investments through diversification effects. In this regard, investment horizon would be an essential feature of efficient portfolio management. A professional portfolio manager, upon making a long position should know, with certainty, the time of making a short position (Blanchet-Scalliet, El Karoui, Jeanblanc, & Martellini, 2008). Factors such as changes in the opportunity set, the consistent behavior of a se

curity market, the effects of exogenous shocks and particularly, the behavior of optimum portfolios in different holding periods can potentially affect the time of exit.

While standard financial theories and empirical studies are essentially focused on the risk reduction benefits of investments through portfolio diversification, less attention has been paid on the investment horizon and the behavior of optimum portfolios in different holding periods. Modern portfolio theory (Markowitz, 1952, 1959) suggests that greater benefits would be available when lower correlation exists between assets' returns. Furthermore, international portfolio theory (Solnik, 1974) implies that more benefits from diversification can be achieved if investors invest across borders.

This study aims to investigate the behavior of optimum international portfolios for East Asian investors when investing in the Middle East emerging equity markets. This study is considerably different from the current literature in different folds as follow:

First, diversification benefits are mostly explored through the co-movement analysis of market indices (Allen & MacDonald, 1995; Bekaert & Urias, 1996; Chiang, Jeon, & Li, 2007; Chiou, Lee, & Chang, 2009; Grubel, 1968; Ibrahim, 2006a, 2006b; Levy & Sarnat, 1970; Syriopoulos, 2004; Vo, 2009). However, in this study, besides using advanced techniques of co-integration, a multi-objective genetic algorithm based on both symmetric (Mean-Variance) and asymmetric (Mean-Lower Partial Moment) measurements of portfolio risk is applied to investigate the international portfolio diversification (IPD) benefits.

Secondly, despite the fact that about (45%) of portfolio inflows to emerging markets are from other major emerging markets (IFSL, 2009; IMF, 2008), there is not much evidence documented between these countries concerning opportunities and benefits of IPD. Specifically, there is no comprehensive evidence on the diversification benefits between the East Asian emerging countries and selected groups of Middle Eastern markets. While advanced economies are more integrated (Bhargava, Konku, & Malhotra, 2004; Chang, Nieh, & Wei, 2006; Kearney & Poti, 2006; Morana & Beltratti, 2008) there is evidence implying that developing economies can still provide diversification benefits for international investors (Chambet & Gibson, 2008; Ibrahim, 2006b; Middleton, Fifield, & Power, 2008; Phylaktis & Ravazzolo, 2005; Tai, 2007).

Thirdly, in the existing literature, the behavior of passive (long-term) and active (short-term) portfolio investors is explored via different styles of bond or stock portfolios (Dierkes, Erner, & Zeisberger, 2010). However, this study contributes to the optimum portfolio selection theory through investigating the behavior of both the intra and inter-regional levels of pure equity portfolios in different holding periods.

Fourthly, as required by international investors, the most liquid indices from all the Middle East and East Asian markets with the longest available period of data are selected.

The findings of this study provide further insights into the possible portfolio diversification benefits for East Asian investors when investing in the Middle Eastern stock markets. The sampled Middle Eastern countries are the world's major oil producers; therefore, these markets can be considered to hedge the volatility of oil prices for those of East Asian oil consumer investors. In addition, if the level of portfolio inflows into the Middle Eastern countries be increased, alternative sources of financing, apart from the oil revenue could be provided for developing economies of the region. This can shield the developing strategies of these countries during the periods of oil price decline (Mina, 2007).

Unlike East Asian emerging countries, there is a salient advantage for the Middle Eastern stock markets, which is the segmentation of this region from developed financial markets (Abraham, Seyed, & Al-Elg, 2001; Assaf, 2003; Elfakhani & Matar, 2007; Hassan, Maroney, Monir El-Sady, & Telfah, 2003; Neaime, 2006; J.-S. Yu & Hassan, 2008). This evidence is consistent with the low level of foreign direct investment (FDI) as a percentage of GDP in the Middle East compared to other emerging countries (Table 1).

Table 1: FDI as a Percentage of GDP in Emerging Regions

	2000	2001	2002	2003	2004	2005	2006	2007
Asia	4.2	3.0	2.4	2.3	2.9	3.2	3.3	2.9
Latin America	4.8	6.6	3.1	2.6	5.0	4.1	3.4	3.7
Eastern Europe	3.7	3.4	3.6	2.9	4.4	4.1	4.7	3.8
Middle East	1.1	1.1	0.8	1.9	2.2	2.9	3.9	3.2
North Africa	1.3	1.1	1.4	2.1	2.6	4.3	5.6	4.7

Source: EIU (2007)

In addition, World Economic Outlook (2009) reported that while the private capital inflows to the Middle East was on average USD 97.75 billion, it was USD 364.62 for the Asian emerging countries for the years between 2001 to 2008. All these features are signaling that the Middle Eastern markets have not realized the expected degree of integration to developed financial markets. Consequently, these equity markets can provide greater IPD benefits for investors from developed markets. However, whether investor from emerging markets in general and East Asian markets in particular can enjoy from portfolio diversification opportunities through the Middle Eastern markets is a crucial question which needs to be empirically investigated.

The correlation coefficients of daily returns within the Middle Eastern markets (Panel A) and between the Middle East and East Asian markets (Panel B) are summarized in Table 2. The average correlation of the daily returns within the East Asian stock markets is 0.443, which marginally reduces to 0.039 when the sample of markets is extended to the Middle Eastern equity markets. Markets heterogeneity resulted from low correlation coefficients may also suggest high segmentation and consequently, possible diversification benefits (Lagoarde-Segot & Lucey, 2007). Korean investors are expected to get the highest diversification benefits with the lowest average correlation with the Middle Eastern markets (0.029). Meanwhile, the possible lowest diversification benefits would be for Malaysian investors, as Malaysian stock market has the highest average correlation with the Middle Eastern market (on average 0.052).

Table 2: Correlation Coefficients of Daily Market Returns

	Bahrain	Kuwait	Oman	Qatar	Saudi	UAE	Middle East
Panel A (Middle East)							
Bahrai	1.000						0.08
Kuwait	0.127	1.000					0.11
Oman	0.128	0.070	1.000				0.12
Qatar	0.034	0.092	0.133	1.000			0.10
Saudi	0.076	0.102	0.164	0.053	1.000		0.09
UAE	0.050	0.157	0.123	0.210	0.069	1.000	0.12
Panel B (Middle East-East Asia)							
China	0.059	0.076	0.050	0.042	0.023	0.074	0.05
Hong	0.037	0.051	0.059	0.039	0.029	0.066	0.043
Indone	0.051	0.042	0.053	0.063	0.007	0.071	0.043
Korea	0.045	0.058	-0.005	0.030	0.018	0.044	0.029
Malays	0.043	0.052	0.049	0.077	0.041	0.032	0.052
Philipp	0.033	0.042	0.038	0.063	-0.009	0.051	0.033
Singap	0.047	0.073	0.003	0.024	0.005	0.049	0.030
Thailan	0.037	0.064	-0.013	0.077	-0.003	0.053	0.032

Average Correlation of Daily returns within the Middle Eastern Stock Markets
Average Correlation of Daily Returns within East Asian Stock Markets
Average Correlation of Daily Returns Between East Asia and the Middle East

The rest of this paper is organized as follows: A brief background of the study is provided in Section 2. The data and the methodology of study are described in Section 3. The empirical results are presented in Section 4, and finally the paper is concluded in Section 5.

Background of Study

One of the most crucial matters in applied finance is *portfolio selection*, which is how to select and arrange a variety of assets in a way which can best fulfill the investors financial ambitions (Huang, 2008). Markowitz (1952) is honored by developing the Modern Portfolio Theory (MPT), which is the first mathematical formulation of the portfolio selection problem, based on risk-return trade-off. According to this theory, the probability distribution of asset returns is known (Vercher, Bermudez, & Segura, 2007). MPT suggests that investors should not select their assets merely according to their unique characteristics. The other crucial element to take into account is how each security is co-related with all other securities (Elton & Gruber, 1997).

Two of the strongest assumptions presented under Markowitz's Mean-Variance (M-V) theory are that asset's returns are normally distributed, and that the utility functions of investors' preferences are quadratic, of course neither of these assumptions holds in practice (Coleman & Mansour, 2005; Estrada, 2006; Grootveld & Hallerbach, 1999; Konno, Waki, & Yuuki, 2002). Furthermore, as Coleman and Mansour (2005) and Zhang and Zhou (2006) maintain in the M-V approach, investors' risk aversion is disregarded by the implied symmetry of the covariance-based measure of risk.

Disappointed with the flaws in the variance approach, scholars have developed other measures of risk to formulate the portfolio optimization problem like Lower Partial Moment (LPM) (Bawa & Lindenberg, 1977). The VaR, the conditional VaR and the expected shortfall are some other instances of downside risk measures that are entered as restraints in portfolio optimization problems (Jarrow & Zhao, 2006).

This research is based on multi-objective problems (MOPs), which consist of two or more objective functions and are optimized by evolutionary techniques. Techniques used in mathematical programming such as linear programming or gradient, encounter some specific limitations when dealing with MOPs. For example, many of these techniques are influenced by the continuity and/or the shape of the EFs.

For the purpose of some mathematical programming techniques, differentiability of the objective functions and the constraints are supposed to be the crucial requirements (Gong & Cai, 2009). What is more, the final solutions achieved through these techniques are very sensitive to their initialization as they are located relatively close to an initial point. Furthermore, application of each mathematical programming technique, leads to a single non-dominated result. Therefore, several runs, each of which commencing from a different initial point, are needed to achieve several elements of the EF (Coello Coello, 2006). Appearance of these shortcomings has called forth efforts to establish the Evolutionary Multi Objective Algorithms in order to search for EFs in multi-objective optimization problems which are too complicated for mathematical programming techniques to solve them.

According to Konak et al. (2006) and Zitzler et al. (2000) in using an evolutionary algorithm for a multi-objective optimization, two main issues must be taken into consideration: The first concern is how the fitness functions and selection process should be accomplished to guide the searching procedure towards the efficient frontier (Quality) and the second, how a diverse population should be maintained to achieve a well-distributed trade-off efficient frontier, and to prevent premature convergence (Spread).

This research aims at modifying the Multiple Fitness Functions Genetic Algorithm (MFFGA) developed by Solimanpur et al. (2004) and Solimanpur and Ranjdoostfard (2009), in order to find the optimal portfolios. Adopting this approach is based on the following reasons:

(a) A systematic uniform design-based approach is considered by MFFGA, to set the weights of objectives;

(b) A multi-directional search is applied by MFFGA in order to find more points distributed along the EF;

(c) The MFFGA approach - unlike most other algorithms in which user-defined or randomly generated vectors are used to search the solution space- uses a uniform design method to construct uniformly directed search vectors; and

(d) The mathematical background of the MFFGA is relatively comprehensive. Thus, MFFGA can be used in many fields as well in finance, and particularly in portfolio optimization problems.

Data and Methodology

Data

This research aims at focusing on the emerging markets of the Middle East and East Asia. Countries which are taken into consideration as samples of Middle Eastern markets include: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and the United Arab Emirates (UAE). All these markets are located around the Persian Gulf and their economic base is primarily due to oil revenue. Due to several factors such as monetary stability, achievement of higher economic growth, deregulation of stock markets, and trade and financial liberalization, these emerging markets have developed considerably in the last decade.

The prominent East Asian equity markets are located in Malaysia, Thailand, the Philippines, Korea, Singapore, and Hong Kong.

The data set of S&P/IFC and S&P/BMI, in the form of daily price indices from July 2001 to the end of August 2008 is used. However, for UAE, Qatar and Kuwait, ADX, DSM 20 and KIC indices is used, respectively, as they are not included in the S&P database. To control the impact of exchange rate, all prices are expressed in US dollars.

Methodology

Long-run Linkage and Short-run Dynamics

One shortcoming of correlation coefficients is that they represent only the short-run relationships, which tend to be unstable over a long period of time, implying that if some markets are integrated over the long-term and diverge considerably in the short-term, the correlation coefficients will not be a reliable criterion to evaluate the markets' co-movements. To avoid this problem, the widely used Johansen (1988, 1991) and Johansen and Juselius (1990) co-integration test based on the Vector Autoregressive (VAR) framework was utilized to identify long-term co-movements between international markets. Ratanapakorn & Sharma (2002) argue that all the smallest eigenvalues are taken into account by λ-trace statistic; thus, it tends to have more power than the maximum eigenvalue statistics. In addition, Johansen and Juselius (1990) indicate that the emphasis should be on λ-trace statistics rather than λ-max statistics when a conflict between these two test statistics occurs; therefore, in this study we rely on the results of λ-trace statistics. Another relevant consideration is the choice of the appropriate lag length as the results of the Johansen-Juselius co-integration test are very sensitive to the order of the VAR model. This study specifies the optimal lag length using the Johansen (1992) suggestion so that the VAR residuals must be Gaussian or serially uncorrelated.

However, before running a co-integration test, the non-stationarity of the data series has to be established. The commonly used unit root tests, Augmented Dickey–Fuller (ADF) test and the Phillips and Perron (PP) non-parametric test, are applied to investigate the presence of stochastic non-stationarity in the data. Following Syriopoulos (2004), ADF and PP tests are applied to the more general regression model (including a drift plus a time trend).

To explore the short-run dynamics, variance decomposition (VDC) test is applied to assess the relative importance of a shock in one market that can be explained by other markets. “Independence” occurs if any market explains a greater proportion of its own forecast error variance than any other markets and “interdependence” occurs when a greater proportion of forecast error variance caused by a shock in one market is explained by one or more of the other markets (Smith & Swanson, 2008).

Optimization Algorithm

This research applies to both Mean Variance (M-V) and the Mean Lower Partial Moment (M-LPM) frameworks in order to find a solution for the international portfolio optimization problem. Delecting the M-LPM approach in addition to M-V is because of the following reasons:

1. M-LPM does not hold the assumption that the returns are normally distributed (Stevenson, 2001)[1].
2. The investors' preferences can be reflected in M-LPM better than the traditional measure, which is variance (Brogan & Stidham Jr, 2005).
3. The use of M-LPM comes up with superior results as compared to variance in constructing international portfolios (Stevenson, 2001).

1. Jarque-Bera's test invalidated the normality hypothesis for all variables.

4. Various risk measures were tested by Estrada (2002, 2006) and Hwang and Pedersen (2004) who finally suggested that downside risk measures are important for analyzing emerging market equity indices.

Essentially, the M-LPM approach involves the optimal selection of equities such that the probability of the portfolio returns *(R_p)* that is falling below the target return (τ) is minimized. Therefore, portfolio optimization problem can be formulated as:

$$\text{Minimize} \quad G(x) = \sum_{i=1}^{N}\sum_{j=1}^{N} x_i x_j LPM(n,i) LPM(n,j)\, r_{ij} = LPM(n,p)$$

$$\text{Maximize} \quad H(x) = \sum_{i=1}^{N} x_i R_i = R_p$$

Subject to

$$\sum_{i=1}^{N} x_i = 1$$

$$x_i \geq 0, \qquad i = 1,2,3,\ldots\ldots, N$$

Where:

$x_i =$	The proportion of portfolio allocated to country i
$R_i =$	The expected return on index of country i
$R_{it} =$	The expected return for index i during period t
$R_p =$	The expected portfolio return
$LPM(n,p) =$	The portfolio risk
$LPM(n,i) =$	$\frac{1}{T-1}\sum_{t=1}^{T}[Max(0,(R_{it}-\tau)]^{n}$
$n =$	The degree of LPM, fixed at 2
$N =$	The number of countries
$\tau =$	The target rate or return, fixed at 0
$T =$	The number of return observation in country i

However, in the M-V framework, the portfolio risk can be calculated with the following equation:

$$\sigma_p^2 = \sum_{i=1}^{N}\sum_{j=1}^{N} x_i . x_j . \sigma_{ij}$$

Where σ_{ij} denotes the co-variance between the returns *i* and *j*.

In order to solve the proposed models and find the EFs, the Multiple-Fitness Function Genetic Algorithm (MFFGA) developed by Solimanpur et al. (2004) and Solimanpur and Ranjdoostfard (2009) is modified and applied.. In this approach, each portfolio is represented by one chromosome with *num_bits* genes for each country. Therefore, for a portfolio with *N* countries, the length of any chromosome would be *N*×*num_bits*.

For the purpose of representing the genes, a binary encoding system is used. If the decoded decimal value of country *I* be v_i, the following equation is defined to calculate the portion of capital allocated to country *i*:

$$x_i = \frac{v_i}{\sum_{i=1}^{N} v_i}$$

In the above formula, x_i is the weight of capital allocated to country *i* and *N*are the numbers of equity markets. Therefore, in the proposed coding system, for all portfolios it is obvious that $x_i \geq 0$ for $i=1, 2, 3 \ldots N$ and $\sum_{i=1}^{N} x_i = 1$, which refer to the automatic satisfaction of the constraints of the optimization problem. This fulfillment will greatly increase the calculation efficiency of the algorithms.

Of course we need to define the *K* fitness functions in our quest for the objective space, in case the objective functions, $LPM(n, p)$ or σ_p and R_p, are represented by f_1 and f_2 respectively, the fitness function of direction *k* would be formed as follows:

$$fit_k(S) = w_{k1} f_1(S) + w_{k2} f_2(S)$$

where the fitness of portfolio *S* with respect to the *kth* search direction is represented by $fit_k(S)$, the value of the first and the second objective functions for portfolio *S*, is indicated by $f_l(S)$ and $f_2(S)$ respectively, and the weights of objective functions are shown by w_{k1} and w_{k2} respectively.

Since the values of risk and return vary in different ranges, it would be possible that an objective with a greater value dominates the contribution of other objectives. Therefore, the objective functions have been normalized as follows:

$$fit_k(S) = w_{k1}h_1(S) + w_{k2}h_2(S)$$

where

$$h_1(S) = \frac{f_1(S)}{\max\{ f_1(S') \mid \forall S' \in \Omega\}}$$

The normalized value of the objective function l for portfolio S is denoted by the function $h_l(S)$ and Ω stands for the set of all portfolios under evaluation.

To form search directions, MFFGA applies a uniform design technique. To calculate search directions, the numbers of directions are considered as levels and objective functions are treated as factors of a matrix. Hence, search directions are calculated as:

$$W = [w_{kl}]_{k\times 2} \quad ; \qquad w_{kl} = \frac{u_{kl}}{\sum_{l=1}^{2} u_{kl}}$$

where $W(K, 2)=[w_{kl}]_{k\times 2}$ is the uniform design matrix. Each row of the matrix W is a search vector and w_{kl} is the weight of the objective function l in fitness function k. The genetic algorithm was programmed in Matlab[1].

The Behavior of EFs

International investors are sensitive about the consistency of equity markets in portfolio diversification. By consistency, we mean the international investors' ability to provide efficient and stable investment opportunities in long and short holding periods. We evaluate this

1. The program consists of eleven function files: one main function and ten sub-functions. The files are available on request.

feature by means of long and short-term behavior of EFs. This research inquires into the long-term behavior of EFs through using monthly returns of market indices from the 2001 to 2008 period. In the case of the short holding period, two years' in-sample data from the 2007 to 2008 period is utilized. The analysis is expanded to two levels: First, the behavior of the long and short-term EFs of the Middle East and East Asian stock markets are compared with one another. Then, the Middle Eastern markets are included in the samples of East Asian markets and the analysis is then repeated. The Mann Whitney U test is used to test for the consistency of the EFs' behavior.

Findings

Table 3 reports unit root tests' results for daily index prices and returns. Both ADF and PP tests suggest that the levels of all variables across the sample countries contain unit roots and thus, follow stochastic trends in their levels. Therefore, all variables are integrated in the first order.

Table 3: Unit Root Tests of Daily Index Prices and Returns

Country	Levels			First Difference		
	ADF		PP	ADF		PP
	P-value	Lag	P-value	P-value	Lag	P-value
Bahrain	0.704	1	0.540	0.0001**	0	0.0001**
Kuwait	0.922	1	0.932	0.0001**	0	0.0001**
Oman	0.589	2	0.506	0.0001**	1	0.0001**
Qatar	0.933	2	0.931	0.0001**	1	0.0001**
Saudi	0.983	0	0.968	0.0001**	0	0.0001**
UAE	0.893	1	0.870	0.0001**	0	0.0001**
China	0.63	0	0.56	0.0001**	0	0.0001**
Hong Kong	0.153	0	0.133	0.0001**	0	0.0001**
Indonesia	0.136	1	0.160	0.0001**	1	0.0001**
Korea	0.818	0	0.783	0.0001**	0	0.0001**
Malaysia	0.728	1	0.727	0.0001**	0	0.0001**
Philippine	0.319	1	0.358	0.0001**	0	0.0001**
Singapore	0.390	1	0.369	0.0001**	0	0.0001**
Thailand	0.870	0	0.870	0.0001**	0	0.0001**

** indicates a stronger rejection at the 1% level.

Long-run Linkage and Short-run Dynamics

One co-integrating vector is observed within East Asian equity markets (Table 4). This indicates that in the long-term neither of the price indices in East Asian stock markets can arbitrarily drift away from other regional markets' indices. Therefore, the possibility of gaining from regional portfolio diversification within East Asian markets will not be noticeable.

Table 4: Tests for the Number of Co-Integrating Vectors within East Asian Stock Markets

Countries in the Group		**H0: r = 0**	**H1: r ≤ 1**	**H2: r ≤ 2**	**H3: r≤ 3**	**H4: r ≤ 4**	**H5: r ≤ 5**	**H6: r ≤6**	**H7: r≤ 7**
East Asia	Trace Stat.	171.6**	114.3	79.4	48.0	30.5	13.9	6.7	1.6
	Critical Value 5%	159.5	125.6	95.8	69.8	47.9	29.8	15.5	3.8

** Rejection of the null hypothesis at the 5% level of significance.

Considering the individual East Asian markets together with the Middle Eastern markets, the null hypothesis of no co-integration is rejected between the groups of "China-Middle East" and "Indonesia-Middle East" stock markets. However, for the rest of the East Asian stock markets there is no evidence to support the long-run co-movements (Table 5). Therefore, with the exception of China and Indonesia, international investors from other East Asian countries with long-term perspective, may get more portfolio diversification benefits when investing in the Middle Eastern equity markets. Though it is found that the stock markets of China and Indonesia are integrated with the Middle Eastern markets, the degree of their integration with this region is much less than with the East Asian markets. Accordingly, the ability of the Middle East stock markets to provide diversification benefits for investors from China and Indonesia would be possible.

Table 5: Tests for the Number of Co-Integrating Vectors

Countries in Group	H0: r = 0	H1: r ≤ 1	H2: r ≤ 2	H3: r≤3	H4:r≤4	H5: r≤5	H6: r ≤6
China, Middle East	139.68**	81.98	48.25	26.40	12.58	4.30	0.23
H. Kong, Middle East	121.89	76.42	46.97	24.55	11.66	3.75	0.31
Indonesia, Middle East	127.55**	83.41	54.61	30.59	13.70	5.33	0.77
Korea, Middle East	115.04	75.74	46.49	26.24	13.90	5.69	0.90
Malaysia, Middle East	125.56	74.77	49.05	28.49	12.87	5.43	0.78
Philippine, Middle East	119.92	76.24	47.88	24.92	13.27	5.45	0.86
Singapore, Middle East	116.13	69.54	44.16	24.16	11.36	4.53	0.60
Thailand, Middle East	121.83	86.09	56.65	29.62	14.42	6.23	0.04

** Indicates rejection of the null hypothesis at the 5% level of significance. Critical values for null hypothesis from Ho to H6 sequentially are: 125.6, 95.8, 69.8, 47.9, 29.8, 15.5, and 3.8.

Table 6 summarizes the VDC results between the Middle East and East Asian markets. The results of using VDC verify that all East Asian equity markets are more sensitive to the shocks on their own regional markets rather than those in the Middle East. However, among all countries in the Middle East, Qatar is the most sensitive market to shocks on East Asian stock markets. This might be a result of the high amount of investments made by Qatar in Indonesia and long-term oil agreements between China and Qatar. VDC results show that China not only plays the greatest influential role in its own region but also, among the Middle East, as on average it can explain (30%) of the error variances in East Asia and (3.2%) of the error variances in the Middle East. Meanwhile, Singapore has the least short-run impact on the Middle Eastern stock markets as on average it can account for only (0.2%) of the error-variances in this region. The impacts of the Middle East markets on East Asia are not noticeable as well. Bahrain, Kuwait, Oman, Qatar, Saudi and UAE can explain on average only (0.3%, 2.6%, 1.1%, 0.4%, 0.2% and 0.3%) of the error variances in East Asia respectively. On the issue of relative importance of short-run impacts of East Asian markets to the Middle East region, the most outstanding one is the impact of China's innovations on Oman (4.2%). This impact is very low compared to the influential role of China on it is own regional countries, which are (70.7%, 20.9%, 29.5%, 30.6%, 17.9%, 27.9% and 12.4%) for Hong Kong, Indonesia, Korea, Malaysia, Philippine, Singapore and Thailand respectively.

Overall, the results of short-run dynamics analysis between the Middle East and East Asian stock markets provide enough evidence for East Asian investors to get more benefits by expanding their international portfolios through equities from the Middle Eastern stock markets.

Portfolio Optimization

In Figures 2 and 3, the effects of including the Middle Eastern stock markets in the sampled East Asian markets can be found. While the M-LPM model pushes the EFs to the left of classical Markowitz M-V model, both M-V and M-LPM models come up with similar results. The EF of East Asian stock markets shifts upward to produce more efficient portfolios once the sample of the Middle Eastern stock markets is added to them. This implies that international investors from East Asian countries can obtain more benefits by inter-regional portfolio diversification compared to the regional diversification.

Although, East Asian stock markets have an inferior EF, they provide wider range of investment opportunities as compared to the Middle East and the sample of the Middle East-East Asian markets.

The dominance of the Middle East EFs under both M-V and M-LPM methods implies that regionally constructed portfolios by the Middle Eastern equities can result in higher portfolio return per unit of risk and lower portfolio risk per unit of return.

Table 6: Variance Decomposition of Stock Index Innovations between East Asia and Middle East (30-days Horizon)

Country	Horizon Days	Percentage of forecast error variance by innovations in:															
		China	H.K.	Indonesia	Korea	Malaysia	Philippine	Sing	Thailand	Bahrain	Kuwait	Oman	Qatar	Saudi	UAE	ME	E. Asia
China	30	87.7	0.3	0.2	1.0	0.0	0.6	4.6	0.3	0.4	3.4	0.6	0.6	0.1	0.1	5.2	7
H. Kong	30	70.7	16.0	0.3	0.1	0.2	0.2	7.6	0.7	0.2	1.5	2.2	0.1	0.2	0.1	4.3	79.8
Indonesia	30	20.9	5.1	60.5	2.0	0.0	2.4	1.7	2.6	1.0	2.5	0.0	0.8	0.1	0.3	4.7	34.7
Korea	30	29.5	8.6	0.4	48.1	0.5	0.1	7.2	0.1	0.3	2.5	2.0	0.1	0.5	0.1	5.5	46.4
Malaysia	30	30.6	10.6	3.5	1.4	46.8	0.9	3.1	0.7	0.1	1.1	0.2	0.5	0.6	0.0	2.5	50.8
Philippine	30	17.9	3.8	7.5	1.6	2.0	53.3	8.4	0.2	0.3	1.9	2.1	0.3	0.1	0.6	5.3	41.4
Singapore	30	27.9	10.8	0.4	2.4	1.9	2.0	50.3	0.3	0.2	2.7	0.8	0.2	0.0	0.0	3.9	45.7
Thailand	30	12.4	4.3	3.6	2.3	3.0	0.1	2.2	64.7	0.0	5.0	1.2	0.2	0.0	1.0	7.4	27.9
Bahrain	30	3.5	0.4	0.4	0.3	0.4	0.1	0.3	0.1	87.9	2.9	0.2	2.9	0.2	0.4	6.6	5.5
Kuwait	30	3.4	0.4	0.4	0.1	0.1	1.5	0.1	0.0	0.4	91.2	0.1	1.2	0.2	1.0	2.9	6
Oman	30	4.2	0.9	3.1	0.1	1.4	0.0	0.0	0.7	2.4	2.6	78.7	0.3	0.1	5.7	11.1	10.4
Qatar	30	3.6	0.2	1.4	0.3	2.8	1.4	0.1	1.6	0.1	1.0	0.6	84.1	0.8	2.0	4.5	11.4
Saudi	30	2.1	0.1	0.2	0.4	0.1	0.6	0.1	0.1	0.0	2.8	1.1	4.7	80.5	7.1	15.7	3.7
UAE	30	2.1	0.4	1.4	1.4	0.6	0.2	0.4	0.4	0.9	1.3	0.7	16.8	0.2	73.3	19.9	6.9
Middle East Ave.		3.2	0.4	1.2	0.4	0.9	0.6	0.2	0.5	0.8	2.1	0.5	5.2	0.3	3.2		
East Asia Ave.		30	6.2	2.3	1.5	1.1	0.9	5.0	0.7	0.3	2.6	1.1	0.4	0.2	0.3		

Table 7: Optimal Capital Allocated to the Middle East and East Asia

	Bahrain	Kuwait	Oman	Qatar	Saudi	UAE	Hong Kong	Korea	Malaysia	Philippine	Singapore	Thailand	Return	Risk
Panel A (M-V Method)														
Min Risk-Return	10.09%	9.22%	11.16%	9.22%	0.53%	15.24%	0.60%	6.35%	12.77%	7.49%	16.84%	0.47%	18.24%	3.83%
Med Risk-Return	0.19%	12.45%	20.75%	24.32%	13.03%	0.58%	1.16%	3.57%	4.05%	5.12%	5.89%	8.88%	23.17%	6.92%
Max Risk-Return	1.22%	6.70%	0.49%	27.53%	30.57%	14.13%	2.07%	3.53%	2.19%	1.46%	0.12%	9.99%	24.14%	12.17%
Panel B (M-LPM Method)														
Min Risk-Return	13.30%	8.14%	14.83%	5.81%	0.29%	12.35%	8.36%	8.07%	13.95%	2.03%	12.43%	0.44%	17.57%	0.72%
Med Risk-Return	16.18%	12.24%	19.61%	21.71%	4.61%	0.13%	4.74%	2.11%	8.55%	3.55%	0.26%	6.32%	21.75%	1.00%
Max Risk-Return	1.98%	6.15%	12.10%	24.31%	16.57%	23.81%	1.79%	2.48%	3.87%	3.57%	1.29%	2.08%	24.05%	1.72%

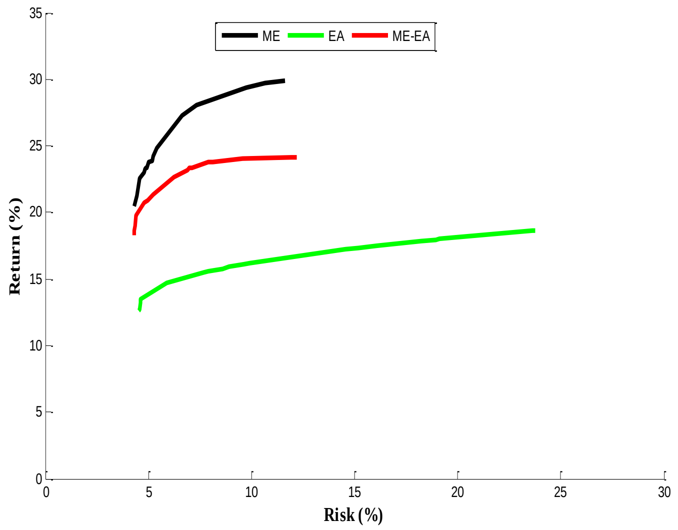

Figure 1: Efficient Frontiers of International Portfolios Using the M-V Framework

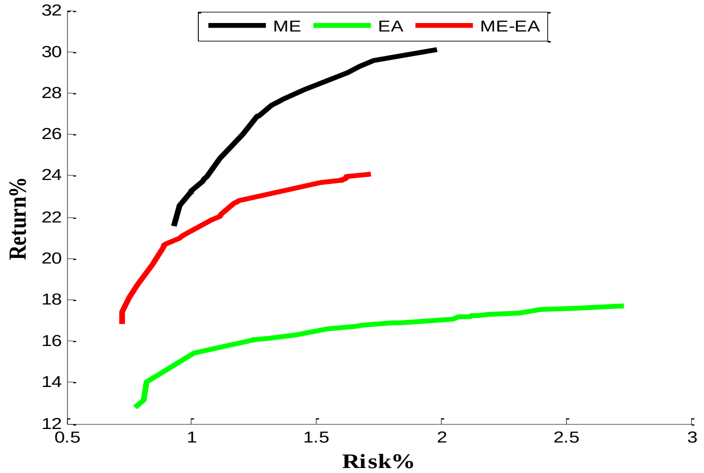

Figure 2: Efficient Frontiers of International Portfolios Using the M-LPM Framework

Three important portfolios from EFs of the ME-EA sample are selected here to provide further realization and to explore the optimal capital allocation among stock market. The selections incorporate the minimum risk-return portfolio, the median risk-return portfolio, and the maximum risk-return portfolio.

Tables 6 summarize the results of optimal capital allocation. While the optimal portfolios produced by the both methods vary in almost the equal range of returns (Return-range $_{M\text{-}V}$ = 5.9%; Return-range $_{M\text{-}LPM}$ = 6.4%), the range of risks for portfolios made by M-V model is significantly larger than those made by M-LPM model (Risk-range $_{M\text{-}V}$ = 8.3%; Risk-range $_{M\text{-}LPM}$ = 1%). This is due to different definition of risk by each of the models such that when the distribution of returns is not normal, dissimilar to M-V model, M-LPM concerns the investor's aversion to negative returns.

In terms of optimal capital allocation, for instance, in the interest of selecting the minimum risk-return portfolio, the results are specified in the first row of Table (Panel A). This portfolio will result in about (18.24%) yearly return with (3.84%) risk. However, the order of capital allocated to each market is being changed by using M-LPM method to fulfill the investor's interest to positive returns.

In general, using both the M-V and the M-LPM approaches the Middle Eastern equity markets potentially attracts more investable capital than the East Asian markets. For example, using the M-V model, if investors are interested in constructing the maximum risk-return portfolio, the total capital which is optimally allocated to each region should be as follows: Middle East (80.63 %) and East Asia (19.37 %) (Table 3, Panel A). These results of the portfolio optimization process strongly highlight the influential role of the Middle Eastern stock markets in providing diversification benefits for international investors from East Asian emerging countries.

Behavior of EFs (Intra-regional)

In the long holding period, when investors aim to diversify their portfolios regionally, the EF of the Middle East dominates the East Asian EFs (Figure 3). This implies that the long-term intra-regionally diversified portfolios by the Middle Eastern equities outperform portfolios constructed by the equities from East Asian markets. Another observation is that the Middle Eastern equity markets provided a larger range of portfolio investment opportunities such that investors who usually hold positions for a half-year or more may have further options of selecting investment choices. However, Figure 4 shows that, the performance line of the Middle Eastern portfolios falls sharply down, moving on EF curve from the lowest risk-return toward the highest risk-return optimal portfolios. This signifies that the increasing rates of risks are not suited to changes of returns among the Middle Eastern optimal portfolios as compared to optimal portfolios of East Asian equity markets.

The intersection point of performance lines in Figure 4 denotes that the Middle Eastern optimal portfolios with monthly risks and returns lower than (0.29% and 2.33%) respectively, behave more efficiently than higher risk-return optimal portfolios.

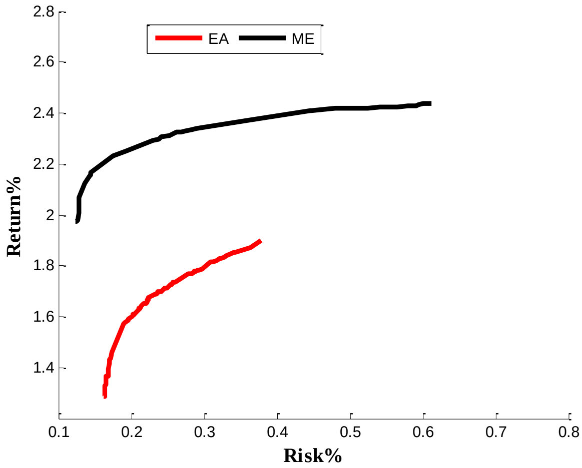

Figure 3: Efficient Frontiers in the Long-term

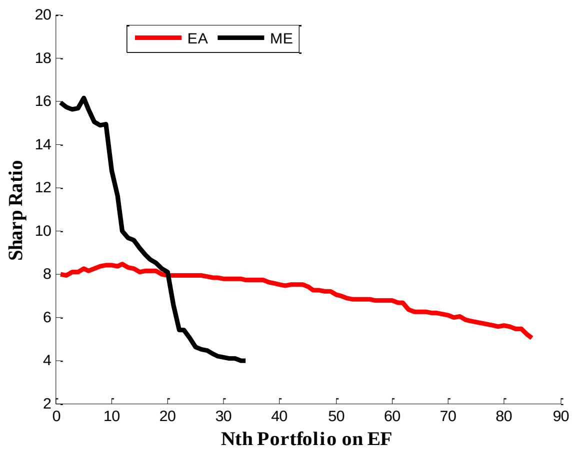

Figure 4: Performance Changing of Optimal Portfolios in the Long-term

In the short holding period, dissimilar to the long-term, the EF of the Middle Eastern markets is dominated by the EF of East Asian markets (Figure 5). It is also understood that the EF of East Asia provides a wider set of portfolio investment opportunities compared to the EF of the Middle East. This implies that in the short holding period the performance of regionally diversified portfolios by the East Asian equities may exceed the performance of those optimal portfolios which are made by the equities of the Middle Eastern markets. Hence, portfolio diversification through East Asian equity markets might be more adequate for high turnover managers such as hedge fund managers who usually turn positions within one to six months.

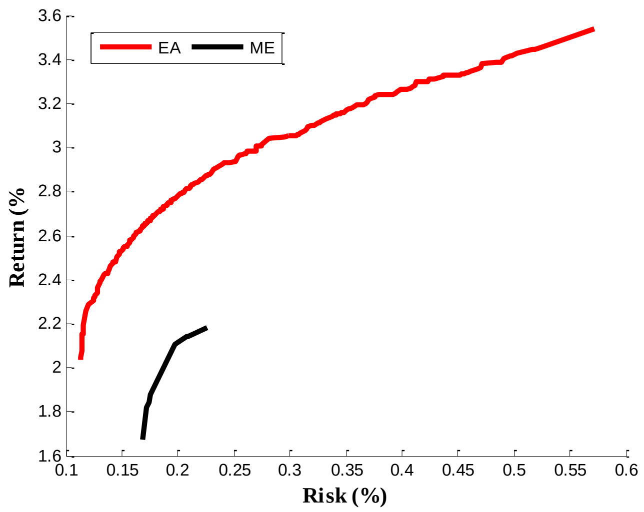

Figure 5: Efficient Frontiers in the Short-term

However, the higher risk-return portfolios of East Asian stock markets were characterized by the lower performances measured by the Sharpe ratio (Figure 6). This means that, taking a short-run investment perspective, the lower risk-return optimal portfolios behaved more efficiently as compared to the higher risk-return optimal portfolios.

Another interesting result is that, even though developed countries have non-dominant EFs in the long and short-terms, their performance lines have a very stable change over different holding periods. This important feature refers to the rational trade-off between risk and return of optimal portfolios constructed in developed stock markets, which is not observed among optimal portfolios of emerging markets.

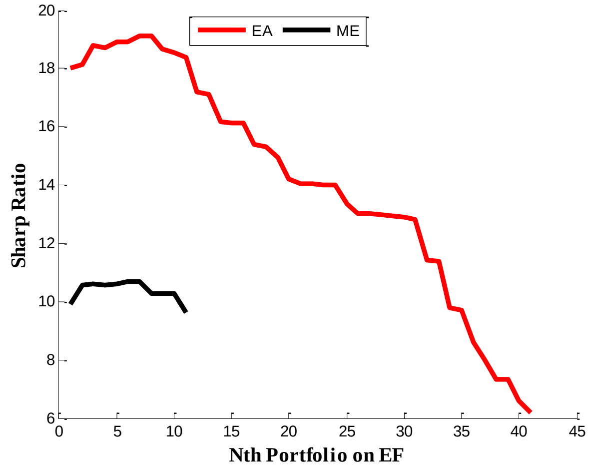

Figure 6: Performance Changing of Optimal Portfolios in the Short-Term

No matter how superior the EFs are; the EFs which are offered by the Middle Eastern and East Asian equity markets do not provides opportunities for choosing the desired investments among a similar set of portfolio risks; therefore, the risks of their optimal portfolios are restricted either in the long-or the short-term. In particular, for East Asian optimal portfolios, a larger set of investment opportunities are provided by the short-term EF. This implies that, although high correlation coefficients exist among the East Asian market returns, it may be still profitable for East Asian investors to diversify their regional portfolios in the short-term.

EFs' Behavior (Inter-regional)

For international investors, investment horizon is of great importance and concern. Therefore, the long and the short-run behavior of EFs among inter-regional optimal portfolios are examined and compared in further analysis. In order to achieve this end, the MFFGA algorithm is applied to obtain the long and the short-term EFs for the Middle East-East Asia (ME-EA) group of equity markets. Figure 7 represents the EFs for inter-regional sample of stock markets.

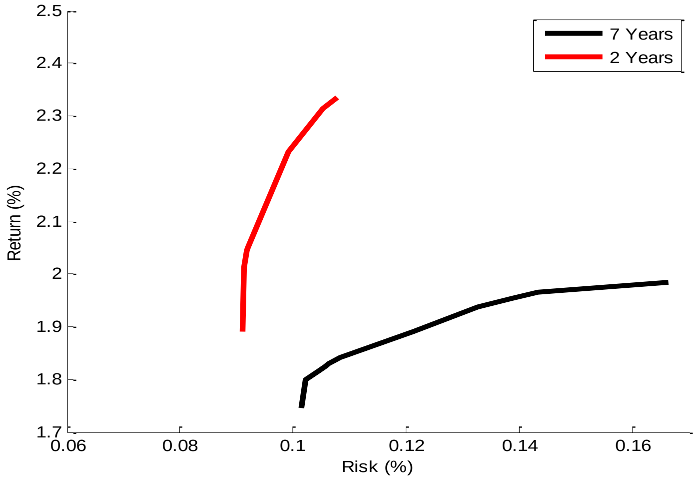

Figure 7: Long-and - Short-term Efficient Frontiers (ME-EA)

The Middle Eastern equity markets offer good opportunities for both the long and the short-term investments to international investors who seek effective strategies for portfolio diversification.. For the sample of ME-EA stock markets a shorter period results in a more superior EF. As a result, proactive mangers of East Asian large institutions such as, trust banks, pension funds and insurance companies of which are normally categorized as long-term investors, the Middle East equity markets might be considered less beneficial avenue not suitable for portfolio diversification. Nevertheless, investment in this area is supposed to be more desirable for those of East Asian's short-term investors like mutual fund managers who have high portfolio turnover and are not fully concerned with increasing the long-term benefits. The long-term EF, on the other hand, renders a wider scope of promising investment opportunities, which are more appealing to investors as they desire to have a long term investment. This tendency is evoked by paying attention to several advantages of long-term investments like receiving accumulative interest, benefiting from dividends which in turn increase the value of investment, being less vulnerable to the consequences of short term volatilities, gaining good rate of return and so on.

In Table 8 we find the results of the Mann Whitney U tests. The hypotheses of equality of returns and of risks between the long and short-term EFs are proved invalid for all intra and inter-regional EFs at the (5%) level of significance. Because the reason is that the *p*-values of Mann Whitney U test for both dimensions of EFs are much below the α-value (0.05). Although for the EFs of the Middle East-East Asia sample the null hypothesis of equality for risks cannot be rejected (*p*-value = 0.118), it is not concluded that the EFs of long and short-terms are similar. This is due to the fact that the null hypothesis of equality for returns is mostly rejected (*p*-value = 0.0001) implying that neither the returns nor the risks of the long and the short-term EFs are statistically equal. Consequently, the long-term optimal portfolios in any of intra or inter-regional samples do not behave in the same way to the short-term optimal portfolios and therefore they cannot offer the same benefits to international investors.

Table 8: Mann Whitney U Test for Equality of Intra and Inter-Regional Efficient Frontiers

	H0:Equality of Returns		**H0:Equality of Risk**	
	Z Statistics	P. Value	Z Statistics	P. Value
Middle East	-5.27	0.0001	-2.860	0.004
East Asia	-14.14	0.0001	-2.25	0.024
ME-EA	-4.671	0.0001	-1.600	0.118*

* Insignificance at the 5% level

Conclusion

This paper evaluates the possible international portfolio diversification benefits of the Middle Eastern equity markets for investors from East Asian emerging markets. More specifically, three important issues were addressed in the research. First, the long-run linkage and the short-run dynamics among market prices were investigated. Second, by using the Multiple Fitness Function Genetic Algorithm, the problem of international portfolio optimization was resolved under both M-V and M-LPM frameworks and through this process the effects of including equities from the Middle Eastern stock markets in international portfolios were assessed. Finally, the behavior of EFs in long and short holding periods was investigated in both intra and inter-regional levels.

In general, the results of using the econometrics approaches and the metaheuristic algorithms are supporting each other. Findings indicate that the possibility of gains from intra-regional portfolio diversification within the East Asian block of countries is minimal; however, the results provide enough evidence to get more benefits by intra-regional diversified portfolios through equities from the Middle Eastern markets.

The results of behavior analysis of the intra-regional EFs also indicate that while, in the short-run, portfolio diversification within East Asian markets are more beneficial, in the long-run, Middle Eastern equities provide better regional portfolios. In the inter-regional level though the short-run EF outperform the long-run EF, the later provides a wider range of investment sets for international investors.

Although the Middle Eastern markets are theoretically believed to offer internal portfolio benefits; in fact , they still receive the smallest portion of international portfolio inflows compared to other emerging regions. This failure to receive a bigger share of international portfolio inflows by the Middle Eastern markets is due to different factors such as political instability in these countries, their weak market micro structure, and finally, small market capitalization in the region. The above mentioned factors are in addition to some general requirements which are of very importance to international investors. These crucial factors include: low transaction costs, market liquidity, wider instrument scope, better information dissemination, market regulation, trading mechanisms and selective investment restrictions. Of course it is up to policy makers to think of and adopt appropriate and pragmatic strategies, which can persuade international investors to play a more active role in these markets.

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