Available Online at ESci Journals
Journal of Business and Finance
ISSN: 2305-1825 (Online), 2308-7714 (Print)
http://www.escijournals.net/JBF

INTERNATIONAL PORTFOLIO CHOICES UNDER UNCERTAINTY: A MONTE CARLO SIMULATION PROCESS

[a]Mourad Mroua, [b]Fathi Abid, [c]Wing K. Wong
[a] *Institute of the Higher Business Studies (IHEC) of Sfax, University of Sfax, Tunisia.*
[b] *Faculty of Business and Economics of Sfax, University of Sfax, Tunisia.*
[c] *Wing Lung Bank, Shaw Campus, Kowloon Tong, Hong Kong Baptist University, Hong Kong.*

A B S T R A C T

This paper examines the impact of estimation errors on the financial portfolios optimization processes and investigates the controversy problem of the international and domestic optimal diversification strategies choice from an American investor's point of view. We introduce the concept of portfolio resampling method and we use the nonparametric stochastic dominance approach based simulated p-values to define an optimal diversification choice. Estimation errors visualization shows that changes in input parameters imply large changes in portfolio composition and reveals considerably modification of MV efficient frontiers shape. The findings show that there exists substantial evidence of the international global diversification benefits. Risk-adverse American investor with an increasing utility function prefers the global international resampled diversification strategy. We find that domestic diversification beats only international major and emerging markets diversification. Dominance relationships between the entirely diversification strategies change according to the risk-aversion coefficient.

Keywords: Optimal portfolios choices, Estimation Errors, Portfolio Resampling, Nonparametric stochastic dominance approach, Monte Carlo and bootstrap p-values simulations.

INTRODUCTION

The mean-variance (MV) portfolio theory of Markowitz (1952) is one of the major developments in the finance theory. It has wide practical implications for the portfolio management and is considered as a tool to construct MV efficient frontiers. While investment decision carries on the MV efficient portfolios, many studies show that the classical optimization algorithm suffers from the error maximization (Michaud 1998) since the expected returns and covariances are assumed to be known with certainty. Naturally, this is not the case in practice and the inputs have to be estimated with the estimation errors. The principal limitation in implementing MV analysis is that the expected return vector and covariance matrix of the asset returns are unknown. Furthermore, the optimal portfolios produced by the method are highly sensitive to the inputs used (Fletcher and Hillier, 2001). In other words, the optimization algorithm is too powerful for the quality of the inputs. This problem does not necessarily stem from the mechanism itself; it calls for a refinement of the inputs. To deal with the estimation errors, a concept called "resampled efficiency" has been introduced. This paper contributes to the literature by providing some insights about the portfolio resampling procedure. We consider the impact of the estimation errors on the optimization of the financial diversified portfolios using the resampled efficiency theory (Scherer, 2004, Michaud and Michaud, 2008). This article describes this new technology, puts it into the context of the portfolio management, and points out some peculiarities of the resampled efficiency approach.

The contribution of this paper is to define an optimal diversification strategy choices based on the improved–adjusted-resampled frontiers. We propose a new methodology combining the resampling method, through the Monte Carlo simulation, the MV optimization algorithm, and the nonparametric stochastic dominance approach, using the Monte Carlo

* Corresponding Author:
Email: mroua_mourad@yahoo.fr

and bootstrap p-values simulations, to resolve the controversy problem choice between the domestic and international diversification strategy.

In this paper, we analyze also an optimal portfolio for an American investor who is concerned about the benefits of the domestic diversified portfolios relative to the international diversified portfolios. A tenet of the modern financial theory related to the works of Markowitz (1952, 1959) is that an investor should construct a diversified portfolio of investments to achieve the most favorable tradeoff between the risk and return. A great deal of research has been done on the diversification benefits achievable via the international investment. However, as world capital markets become increasingly more integrated, a question arises as to whether an investor can obtain more gains from the international diversification comparing to the domestic diversification. The preference of the international investors for the domestic stocks remains a subject of controversy, since many studies indicate that greater profits can be made by the international diversification. Home bias towards holding domestic financial assets continues to be an important phenomenon of the global financial markets up to the present moment. Although portfolio theory prescribes that optimal portfolios should be well diversified internationally, in practice investors prefer to invest in the domestic assets. Many studies document the benefits of international diversification (Solnik 1995, Li, Sarkar, and Wang 2003, Meyer and Rose 2003, Driessen and Leaven 2007, Chiou 2009). Nevertheless, in spite of the international diversification benefits, most investors hold nearly all of their wealth in the domestic assets (French and Poterba 1991, Tesar and Werner 1995, Antoniou, Olusi, and Paudyal 2010). Since the optimal choice between the domestic and international diversification is considered as a problem for an American investor, our contribution is to evaluate the dominance relationships between the domestic (DOD), international global (IND), international major (IMD), and international emerging (IED) markets, efficient resampled diversified portfolios to build a framework for resolving the problem of the optimal resampled diversification strategy choice.

Another critical and important issue regarding the international and domestic diversification is the appropriate framework for assessing their benefits. The suitable decision rule used to identify the optimal investment strategy is considered as another problem. Traditionally, empirical portfolio analysis has focused on the MV characteristics of assets. Although the contribution of the traditional models, market instability though the new financial products introduction leads to the violation of the MV hypotheses (Porter and Gaumnitz 1972, Rose, Meyer and Li 2005). The MV approach, where decision makers are assumed to have quadratic utility functions with negative second derivatives, has been widely criticized. The criticisms include restrictions on the type of the risk preference implied and the normality of the data required. Further, the quadratic utility function implies that beyond some wealth level the investor's marginal utility becomes negative. In contrast, the stochastic dominance criterion (SD) can be used as an alternative method to examine portfolios construction and their ranking since it satisfies the general utility function and takes into consideration all distributional moments in the comparisons (Hadar and Russel, 1969, Hanoch and Levy, 1969 and, Rothschild and Stiglitz, 1970). Besides, the SD technique uses the entire probability density function rather than a finite number of moments so it can be considered less restrictive. There are no assumptions made concerning the form of the return distributions and not much information on the investor preferences is needed to rank alternatives. In a different way to the common literature works, this paper applies the nonparametric SD approach to define the dominance relationships between different resampled diversified portfolios in order to define an optimal investment choice.

The main objective of this paper is to examine the impact of the estimation errors on the portfolio optimization processes by considering the ambiguity and instability problems in the input parameters. Besides, we try to resolve the problem of the optimal investment strategy choice using a nonparametric SD approach basing on the MC and bootstrap simulated p-values. To remove the impact of the estimation errors, the adjusted resampled procedure will be introduced in the portfolio optimization to formulate the efficient frontiers of the entire diversification strategies; domestic, international global, only international major and emerging markets. Using a data set consists on the American and Asian geographical blocks of the financial market indices combining 19 emerging (E) and major (M) markets and 27 American stocks from 1993 to 2007, the empirical results show that the estimation errors consideration implies the changes of the MV efficient frontiers shape. Though MV optimization could not be used to draw any preference between international and domestic diversification, the empirical findings suggest the usefulness of the SD approach to rank portfolios and define the optimal choice. Further, the results confirm the performance of the resampled international global diversification strategy to the domestic investors. In fact, for a risk level higher to 30 percent, the risk-adverse American investor having an increasing utility function prefers the global international to the domestic resampled diversification strategy. Besides, we find that the domestic resampled diversification strategy beats the only international major and emerging markets diversification strategies. Referring to the SD order's relationships generated, the American investor, having an increasing utility function, diversifies only 15 percent of his wealth abroad in the major and emerging markets. The SD analysis suggests that the global international diversification dominates entirely the major and emerging markets diversification strategies for the U.S. risk-adverse investor having an increasing utility function. Finally, the findings of the SD tests suggest that the risk-adverse U.S. investor, having an increasing utility function prefers to diversify 45 percent of his wealth in the major markets rather than in the emerging markets.

The remainder of this paper is as follows. Section 2 advances the literature review relating to the motivations and the importance of our study. Section 3 presents the data description, the research hypotheses and methodology based on the resampled efficiency and the SD approach. Section 4 discusses the empirical results. Section 4 presents the empirical results and the fifth section summarizes and concludes.

LITERATURE REVIEW

While theoretically important for modern finance, MV optimization's sensitivity to uncertainty in risk-return estimates typically results in an unstable asset management framework, ambiguous portfolio optimality, and poor out-of-sample performance. The resampled efficiency technique introduces the Monte Carlo (MC) resampling and the bootstrapping methods into MV optimization to more realistically reflect the uncertainty in investment information taking into account the estimation errors. In this way, Jobson and Korkie (1980, 1981), Best and Grauer (1991) and Chopra and Ziemba (1993) investigate the impact of estimation errors on the optimal allocation weights in the portfolio allocation. They find that the composition of the optimal portfolios is very sensitive to the changes in the expected returns, variances and covariances. Moreover, the authors introduce the concept of the portfolio resampling using MC method to analyse the effect of the sample size on the estimation errors. Michaud (1998) notes that MV optimizers are estimation errors maximizers. To deal with the estimation errors, the author introduces the resampled efficiency to generate new inputs parameters' leading to construct the resampled efficiency frontier. Markowitz and Usmen (2003) compare the Michaud resampling with MV optimizer model using improved inputs by taking into account the uncertainty problem in the input parameters optimization. Their experiment reveals that the Michaud's resampled efficiency frontier produces portfolios with more diversified collections of stocks and better returns for a given level of risk. Scherer (2002, 2004) reviews the portfolio resampling methodology and find that that the optimizers are far too powerful for the quality of the inputs. In fact, the resampling remains an interesting heuristic to deal with the important problem of error maximization. Ceria and Stubbs (2006) show that the portfolio managers who rely on MV efficiency often find that their portfolios are unintuitive or do not behave well. The empirical findings suggest that the estimation errors can affect the quality of the portfolio as result as error maximization in the classical portfolio optimization. Abu Mansor et al. (2006) apply the resampled efficiency methodology introduced by Michaud (1998) to compare the optimal portfolio based on the MV and resampled efficiency. They find that the resampled efficiency performed well with the data having the least estimation errors for equity portfolio. To reduce the impact of the estimation errors on the optimal portfolio composition, Becker et al. (2009) compare the resampled efficiency of the performance of traditional MV optimization with the Michaud's estimate and find that the Markowitz's approach outperforms the Michaud's on average. Bai et al. (2009a,b, 2011b) find that the traditional return estimate is always larger than its theoretical value with a fixed rate depending on the ratio of the dimension to sample size. They further propose a new method for reducing this error by incorporating the bootstrap approach into the theory of a large dimensional random matrix. Their bootstrap-modified estimator analytically corrects the overestimation and is proportionally consistent with the theoretical return parameter.

Home bias towards holding domestic financial assets continues to be an important phenomenon of global financial markets up to the present moment. Although portfolio theory prescribes that optimal portfolios should be well diversified internationally, in practice investors prefer to invest in domestic assets. Not surprisingly, since portfolio diversification depends on the correlations between the return distributions of the individual securities, which tend to be lower between countries, the gains from the international diversification have been found to be large. As a consequence of the market liberalisation, the investors seem to prefer financial emerging and major markets. Despite greater integration of the international capital markets, investors continue to hold portfolios largely dominated by the domestic assets. The preference of the international investors to the domestic stocks remains always a subject of controversy in spite of the profits relating to international diversification. Li et al. (2003) study the international diversification benefits for the U.S. investors basing on the developed and emerging market countries. The empirical results show that the international diversification benefits remain substantial for the U.S. equity investors when they are prohibited from short selling. The integration of world equity markets reduces, but does not eliminate, the diversification benefits of investing in emerging markets. The diversification process in domestic market continues to be advantageous for the local investors. Driessen and Laeven (2007) emphasize how the benefits of international portfolio diversification differ across countries from the perspective of a local U.S. investor. They find that the benefits of investing abroad are largest for investors in developing countries, including when controlling for currency effects. Most of the benefits are obtained from investing outside the home market. Chiou (2008) investigates the comparative benefits of international diversification in various countries and shows that investors in less developed countries, particularly East Asia and Latin America, benefit more than those in developed countries from both regional and global diversification. Chiou (2009) examines the optimal international diversification benefits for the U.S. investor while considering various portfolio constraints and find that international diversification beats the benefits of the local investment even though the global financial market has become increasingly integrated.

The appropriate decision rule used to identify the optimal investment strategy is considered as another critical problem. Because of the violation of the MV hypotheses, Hadar and Russel (1969), Hanoch and Levy (1969) and Rothschild and Stiglitz (1970) introduce the SD criterion to compare the different prospects as the SD approach satisfies the general utility function and takes into consideration all distributional moments in the comparisons. Anderson (1996, 2004), Davidson and Duclos (2000), Bai et al. (2011a), among other, note that, because of the critical assigned to the discrete methods, the nonparametric SD approach basing on simulated statistics and p-values procedures are expanded. In this way, Barrett and Donald (2003) and Abhyankar et al. (2009) extend the SD tests based on the MC and bootstrap methods to simulate dominance statistics and p-values to advance a comparison of two investment strategies.

METHODOLOGY

Data description: The data analyzed in this paper are daily continuously compounded returns, for stocks and market indices in the period from August 1993 to August 2007. Daily closing prices of 27 American stocks obtained from CRSP[i] are used to form various domestic diversified portfolios. To form international (both major and emerging) diversified portfolios, we use data obtained from Datastream including two financial blocks: emerging (E) and major (M) markets, and two geographical blocks: North and Latin American countries and Asian countries. The first financial block consists of markets from United-States^M, Canada^M, Argentina^E, Brazil^E, Mexico^E, Venezuela^E whereas the second block consists of markets from China^E, Hong-Kong^M, India^M, Indonesia^E, Japan^M, South Korea^M, Malaysia^M, Pakistan^E, Philippines^E, Sri Lanka^E, Singapore^M, Taiwan^E, and Thailand^E, respectively. To avoid the exchange rate bias, all indices are expressed in US dollar, see, for example, Geert et al. (2005).

Resampled and mean-variance efficiency: In this study, we introduce the estimation errors in the portfolio optimization algorithm by using resampling procedure. We formulate the efficient portfolios for the four investment strategies by adopting the MC measure called portfolio resampling. To generate the random return variables of all the sample assets, we use the following Brownian process:

$R_{it} = \mu_i + \sigma\varepsilon_{it}$ for i=1,2,…,N and t=1,2,…,T; (1)

where R_{it} is the return of the asset i at time t, μ_i is the mean vector return of the original data, σ is the computed standard deviation, and ε_{it} is the normally distributed random noise.

Referring to Fabozzi et al. (2007), the resampled efficient frontiers construction is resumed according to the following algorithm:

Step 1: Estimate the mean vector, μ_N, and covariance matrix, Σ_N, from historical data.

Step 2: Draw N random samples R times from the multivariate distribution $N(\mu_N, \Sigma_N)$ and use these data to estimate a new mean returns vector $\hat{\mu}_N$ and a new covariance matrix $\hat{\Sigma}_N$.

Step 3: Calculate an efficient frontier from the input parameters from Step 2 over the interval from portfolio with minimum risk to portfolio with maximum risk. The interval is partitioned into M equally spaced intervals and record the weight vector $w_{Mi}= w_{1,i},\ldots,w_{M,i}$ of N assets for each of M portfolios for each simulation i.

Step 4: Repeat Steps 2 and 3 R times. We obtain R resampled efficient frontier giving R w_{Mi}'s.

Step 5: Calculate the resampled portfolio weights vector w_M^{RES} as the mean of w_{Mi} weights vectors:

$$w_M^{RES} = \frac{1}{R}\sum_{i=1}^{R} w_{Mi}, \qquad (2)$$

and evaluate the resampled frontier with the mean vector and covariance matrix from Step 1.

We note that the number of draws R (R=1000 times in our study) corresponds to the uncertainty in the inputs used. As the number of draws increases, the dispersion decreases and so do for the estimation errors, the difference between the original estimated input parameters and the sampled input parameters (Scherer, 2004). The number of portfolios M can be chosen freely according to how well the efficient frontiers are being depicted.

Stochastic Dominance Approach: To overcome the limitations of the traditional MV criteria (Bai et al., 2011a), SD provides a general set of rules for evaluating the performance of financial assets. The SD approach has been demonstrated to be a powerful tool in both theory and applications. Its theory has been continually developed over the last four decades, and many SD comparisons have been carried out empirically; see, for example, Fong et al. (2005, 2008), Broll et al. (2006), Wong et al. (2006, 2008), Abid et al. (2009, 2013), and Lean et al. (2007, 2010) and the references therein for more information.

Consider two investment prospects (or portfolios), denoted by *X* and *Y*. We let *F* and *G* be their corresponding cumulative distribution functions, respectively, which can also simply be called distribution functions. Suppose that the cumulative probability of attaining any return in *X* is always smaller than that of *Y*. That is, the distribution *F* lies below the distribution *G*. In this situation, regardless of the complexity of the distributions, as long as investors are non-satiated, no one should buy prospect *Y*, since investors are expected to obtain higher expected utility by investing in prospect *X*.

The most commonly used SD rules that correspond to the three most widely used utility functions are first-, second-, and third-order SD, denoted as FSD, SSD, and TSD, respectively. By applying the SD rules, we can examine the entire distributions of returns, not just a particular parameter such as mean, variance, skewness, or kurtosis. We define the SD rules as follows (Sriboonchitta et al., 2009):

Definition 1: *X dominates Y by FSD (SSD, TSD), denoted by* $X \succeq_1 Y$ $(X \succeq_2 Y, X \succeq_3 Y)$ *if and only if* $F_1(x) \le G_1(x)$ $(F_2(x) \le G_2(x), F_3(x) \le G_3(x))$ *for all possible returns* x. *In addition, if the strict inequality holds for at least one value of* x, *X dominates Y strictly by FSD (SSD, TSD), denoted by* $X \succ_1 Y$ $(X \succ_2 Y$, $X \succ_3 Y)$, *where* F_2 *and* G_2 *are the areas under F and G, and* F_3 *and* G_3 *are the areas under* F_2 *and* G_2*, respectively.*

Let $u(R)$ be the investor's utility function with respect to return R. We define the class of utility functions as follows:

Definition 2: $n = 1,2,3,$ $U_n(U_n^S)$ *are the sets of the utility functions* u *such that* $U_n(U_n^S) = \{u : (-1)^{i+1}u^{(i)} \ge (>) 0, i = 1,\cdots,n\}$, *where* $u^{(i)}$ *is the* i^{th} *derivative of the utility function* u.

For $n = 1,2,3,$ we call investors the nth order risk averters if their utility functions u in U_n in which the first order risk averters exhibit non-satiation $\left(u^{(1)}(R)\geq 0\right)$, the second order risk averters are non-satiated and risk averse $\left(u^{(2)}(R)\leq 0\right)$, while the third order risk averters exhibit non-satiation, risk aversion, and decreasing absolute risk aversion (DARA) $\left(u^{(3)}(R)\geq 0\right)$ ii. The SD rules above are consistent with the principle of expected utility maximization (Hanoch and Levy, 1969; Li and Wong, 1999). That is, for $n=1,2,3$, $F_n \leq G_n$ if and only if the expected utility on X is larger than that of Y for any nth order ($n=1,2,3$) risk averter, inferring that the nth order risk averters prefer X to Y. If a stochastically dominant asset exists, then investors will always possess higher expected utilities under the dominant asset than under the dominated asset. Consequently, the dominated asset should not be chosen. We note that a hierarchical relationship exists in SD: FSD implies SSD, which in turn implies TSD. However, the converse may not be true: the existence of SSD does not imply the existence of FSD. Likewise, the existence of TSD does not imply the existence of SSD or FSD. Thus, only the lowest dominance order of SD is reported (Wong, 2007; Wong and Ma, 2008).

For the four investment strategies: domestic (DOD), international global (IND), international major (IMP) and international emerging (IED) diversified resampled efficient portfolios, we are going to test the dominance between the portfolios in the following pairs: (DOD, IND), (DOD, IMP), (DOD, IED), (IND, IED), and (IMP, IED). We only list the hypotheses for (DOD, IND) as follows: For j=1,2,3, we proceed to specify the following hypotheses:

Hypothesis H_{0j}^{1}: DOD dominates (not strictly) IND (IMP, IED) in the sense of the j order stochastic dominance, and

Hypothesis H_{0j}^{2}: IND dominates (IMP, IED) (not strictly) DOD in the sense of the j order stochastic dominance.

To complement the above hypotheses, we state the following hypotheses which are equivalent to H_{0j}^{1} and H_{0j}^{2}, respectively:

Hypothesis $H_{0}^{1'}$: the jth order risk averters (not strictly) prefer DOD to IND (IMP, IED) , and

Hypothesis $H_{0}^{2'}$: the jth order risk averters (not strictly) prefer IND (IMP, IED) to DOD.

In this study, we adopt both MC and bootstrap methods to simulate the p-values of the SD test statistic to test the above-mentioned hypotheses. Let F and G be the cumulative distribution functions of the DOD and the IND, respectively. Accepting H_{0j}^{1} infers that F dominates G (not strictly) at order j, denoted by $F \succeq_j G$. On the other hand, accepting H_{0j}^{2} infers that G stochastically dominates F (not strictly) at order j, denoted by $G \succeq_j F$. We state the possible situations for accepting/rejecting H_{0j}^{1} and H_{0j}^{2} for DOD and IND in the following property:

Property 1: For j = 1,2, and 3, we have:

a) Do not reject H_{0j}^{1} but reject H_{0j}^{2}, implying that F (DOD) dominates G (IND) strictly, denoted by $F \succ_j G$, at the j order;

b) Reject H_{0j}^{1} but do not reject H_{0j}^{2}, implying that G (IND) dominates F (DOD) strictly, denoted by $G \succ_j F$ at the j order;

c) Do not reject both H_{0j}^{1} and H_{0j}^{2}, implying that there is no dominance between F and G, and the distributions of F and G are not rejected to be the same; we denote this situation by $F=G$; and

d) Reject both H_{0j}^{1} and H_{0j}^{2}, leading us to conclude that F and G do not dominate each other and their distributions may not be the same, denoted by $F \neq G$.

The above property enables us to test the following hypotheses:

$H_0: F=G$, $H_A: F \neq G$, $H_{A1}: F \succ_j G$,and $H_{A2}: G \succ_j F$,

Where F and G are the cumulative distribution functions of DOD and IND, respectively. We note that accepting H_A here only when both H_{A1} and H_{A2} are rejected. Thus, Part (a), (b), (c), and (d) of Property 1 becomes accepting H_{A1}, H_{A2}, H_0, and H_A, respectively. The hypotheses H_{A1}, H_{A2}, H_0, and H_A for other pairs of portfolios, e.g. DOD/IMD and/or IED, IND/ IMD and/or IED, and IED/ IMD, can be obtained similarly.

Stochastic Dominance approach and Monte Carlo and Bootstrap P-Values: In this paper, we compare the statistical characteristics of the three international diversification with the domestic diversification from the perspective of the U.S investors. We apply the MC and bootstrap methods to simulate the p-values of the SD test statistics that compare two candidate cumulative distribution functions at all points in the paired sample. We assume that the prospects being studied are independent and observations drawn from the prospects are identically and independently distributed. We use integral operator to represent various orders of SD. To test for H_{0j}^1, we adopt the following hypotheses:

H_{0j} : $\Im_j$ (z;G) ≤ $\Im_j$ (z;F) for all z ; and H_{1j} : $\Im_j$ (z;G) > $\Im_j$ (z;F) for some z ; (3)

where $\Im_j$(.;i) is defined as an empirical cumulative distribution function i (i=F,G) at order j for j=1, 2, 3. For i=F and G and for j=1,2,3 respectively, $\Im_j$(.;i) are the estimates of *F, G, F_2 , G_2, F_3 , G_3*. The null hypothesis signals that G stochastically dominates F (not strictly) at the j[th] order, denoted by $G \succeq_j F$. While the alternative is that stochastic dominance fails at some points. On the other hand, to test for H_{0j}^2, we use adopt the following hypotheses to test the opposite direction of the dominance:

$H_{0j}^{'}$: $\Im_j$ (z;F) ≤ $\Im_j$ (z;G) for all z ; and

$H_{1j}^{'}$: $\Im_j$ (z;F) > $\Im_j$ (z;G) for some z. (4)

We now illustrate how to test for H_{0j} and H_{1j}. The test for $H_{0j}^{'}$ and $H_{1j}^{'}$ can be obtained similarly. We let

$$\Im_j(z;\hat{F}_N) = \frac{1}{N}\sum_{i=1}^{N}\Im_j(z;1_{x_i}) = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{(j-1)!}1(X_i \le z)(z - X_i)^{j-1}, \text{ and}$$

$$\Im_j(z;\hat{G}_M) = \frac{1}{M}\sum_{i=1}^{M}\Im_j(z;1_{y_i}) = \frac{1}{M}\sum_{i=1}^{M}\frac{1}{(j-1)!}1(Y_i \le z)(z - Y_i)^{j-1} \quad j=1,2,3. \quad (5)$$

To test the equality of the two distributions, we first use the test statistic KS1:

$$\bar{S}_{j,r}^{F} = \max_{t_k}\frac{1}{\sqrt{N}}\sum_{i=1}^{N}(\Im_j(t_k;1_{X_i}) - \Im_j(t_k;\hat{F}_N))U_{i,r}^{F} \text{ and } \bar{S}_{j,r}^{G} = \max_{t_k}\frac{1}{\sqrt{M}}\sum_{i=1}^{M}(\Im_j(t_k;1_{Y_i}) - \Im_j(t_k;\hat{G}_M))U_{i,r}^{G} \quad (6)$$

to generate the MC simulated p-values. Thereafter, we use the test statistic KS2:

$$\bar{S}_{j,r}^{F,G} = \max_{t_k}\sqrt{\frac{NM}{N+M}}\sum_{i=1}^{N}((\Im_j(t_k;1_{Y_i}) - \Im_j(t_k;\hat{G}_M))U_{i,r}^{G} - (\Im_j(t_k;1_{X_i}) - \Im_j(t_k;\hat{F}_N))U_{i,r}^{F}) \quad (7)$$

to test the dominance between the two empirical distribution functions.

We denote $\{U_i^F\}_{i=1}^N$ and $\{U_i^G\}_{i=1}^M$ the simulated processes representing two sequences of iid N(0,1) random variates which are independent from the samples being considered. In addition, we let $\{U_{i,r}^F\}_{i=1}^N$ and $\{U_{i,r}^G\}_{i=1}^M$ be the rth samples of U_i^F and U_i^G, respectively, where r=1,…,R is the number of replications used in the simulation process. We apply 1000 replications in the simulation process, each process is assumed to follow the independent Brownian bridge process stated in (1).

The approximate p-values and the decision rules for rejecting the null hypothesis are given as follows:

Reject H_{0j} if

$$\hat{P}_j^F \cong \frac{1}{R}\sum_{r=1}^{R}1(\bar{S}_{j,r}^F > \hat{S}_j) < \alpha \text{, and}$$

Reject H_{0j} if

$$\hat{P}_j^{F,G} \cong \frac{1}{R}\sum_{r=1}^{R}1(\bar{S}_{j,r}^{F,G} > \hat{S}_j) < \alpha \text{, j=1,2,3;}$$

where R is the number of replications used in the simulation and α is the specified significance level. If p-value is higher than the levelα, we accept H_{0j}; otherwise, we reject H_{0j}.

In addition, we proceed to use three different methods of simulation based on bootstrap technique. For testing the equality of two distributions, F and G, being examined, we first apply the bootstrap approach by using the test statistic KS1 defined in (6) to compute the distributions of the random returns from F and G so that the statistic become KSB1 as shown in the following:

$$\overline{S}^{F}_{j,b} = \sqrt{N}\sup_z((\Im_j(z;\hat{F}^*_N) - \Im_j(z;\hat{F}_N)) \text{ and } \overline{S}^{G}_{j,b} = \sqrt{N}\sup_z((\Im_j(z;\hat{G}^*_M) - \Im_j(z;\hat{G}_M)). \quad (8)$$

Thereafter, we adopt the bootstrap approach by using the second test statistic KS2 in (7) to test SD between empirical cumulative distributions and become KSB2 as shown in the following:

$$\overline{S}^{F,G}_{j,b1} = \sqrt{\frac{NM}{N+M}}\, \underset{z}{Sup}\left(\Im_j(z;\hat{G}^*_M) - \Im_j(z;\hat{F}^*_N)\right). \quad (9)$$

Finally, we will use the third test statistic, denoted as KSB3, to justify the estimation.

$$\overline{S}^{F,G}_{j,b2} = \sqrt{\frac{NM}{N+M}}\, \underset{z}{Sup}\left((\Im_j(z;\hat{G}^*_M) - \Im_j(z;\hat{G}_M)) - (\Im_j(z;\hat{F}^*_N) - \Im_j(z;\hat{F}_N))\right) \quad (10)$$

In each of the three bootstrap-based simulation methods described above, we are interested in computing the probabilities that the test statistics using random variables exceeds the critical values of the test statistics obtained by applying bootstrapping technique on the empirical samples. The exact p-values and the corresponding decision rules for rejecting the null hypotheses in the case of KSB1, KSB2, and KSB3, respectively, are:

Reject H_{0j} if $\tilde{P}^F_{j,b} \cong \frac{1}{R}\sum_{r=1}^{R} 1(\overline{S}^F_{j,b,r} > \hat{S}_j) < \alpha$,

Reject H_{0j} if $\tilde{P}^{F,G}_{j,b1} \cong \frac{1}{R}\sum_{r=1}^{R} 1(\overline{S}^{F,G}_{j,b1,r} > \hat{S}_j) < \alpha$, and

Reject H_{0j} if $\tilde{P}^{F,G}_{j,b2} \cong \frac{1}{R}\sum_{r=1}^{R} 1(\overline{S}^{F,G}_{j,b2,r} > \hat{S}_j) < \alpha$.

To sum up, we use two test statistics, KS1 and KS2, by employing the MC simulation and adopt three test statistics, KSB1, KSB2, and KSB3, by applying the bootstrap simulation to obtain the p-values of the tests in order to test for the existence of any order of SD. We note that in the case of first-order SD, since analytic solution is available, we are not required to use either simulation or bootstrapping to obtain the exact p-value.

EMPIRICAL RESULTS ANALYSIS

Resampled and mean-variance efficiency approach:

We first adopt the resampled and MV efficiency approaches to obtain the MV and resampling efficient frontiers for the four diversification strategies and display the frontiers in Figures 1 and 2, respectively. The figures examine the impact of the estimation errors on the efficient portfolios optimization and consequently on the investment strategy decision choices.

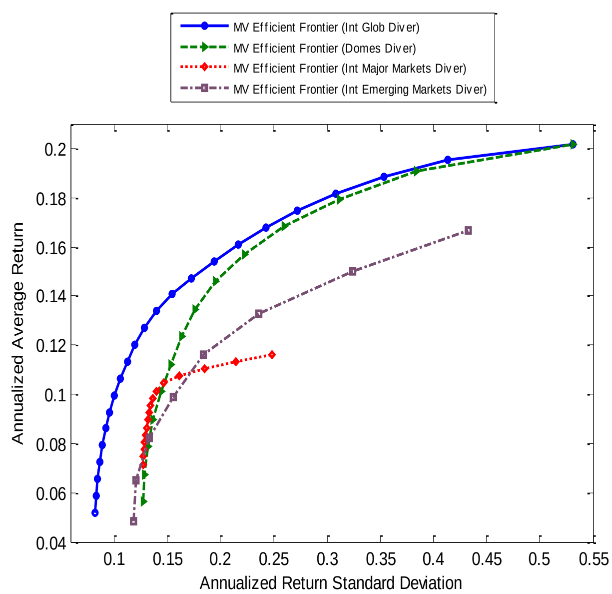

Figure 1. Mean-variance efficient frontiers of various diversification strategies (DOD, IND, IMP, and IED).

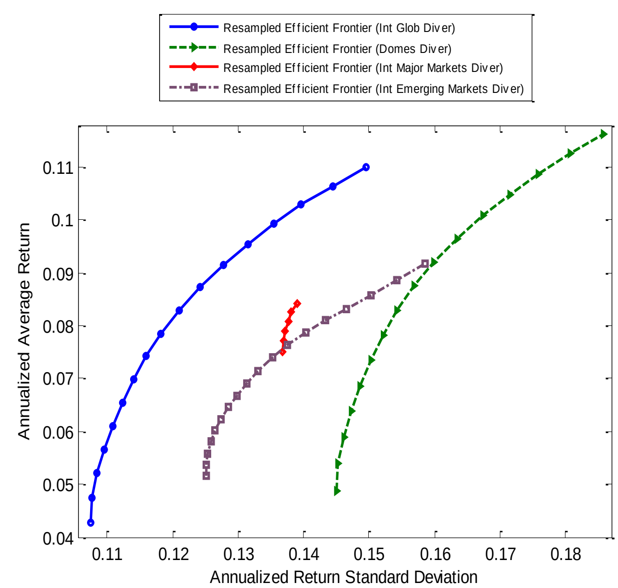

Figure 2. Resampled efficient frontiers of various diversification strategies.

Our results reveal that the simulated efficient frontier is not consistent with the efficient frontier intuition and may not monotonically increase in the expected return with increasing risk. Moreover, the curve of the resampling frontier is remarkably short comparing with MV efficient frontier.

Since addressing estimation errors is an important issue, to make comparison easier we apply the resampled adjusted method to construct new frontiers named improved–adjusted-resampled frontiers. Resampled adjusted method uses the expected return levels of each portfolio located on the MV efficient frontier rather than the return levels of the resampling portfolios generated from simulation by using the quadratic optimisation procedure. Figure 3 illustrates the improved–adjusted-resampled frontiers for the four diversification strategies.

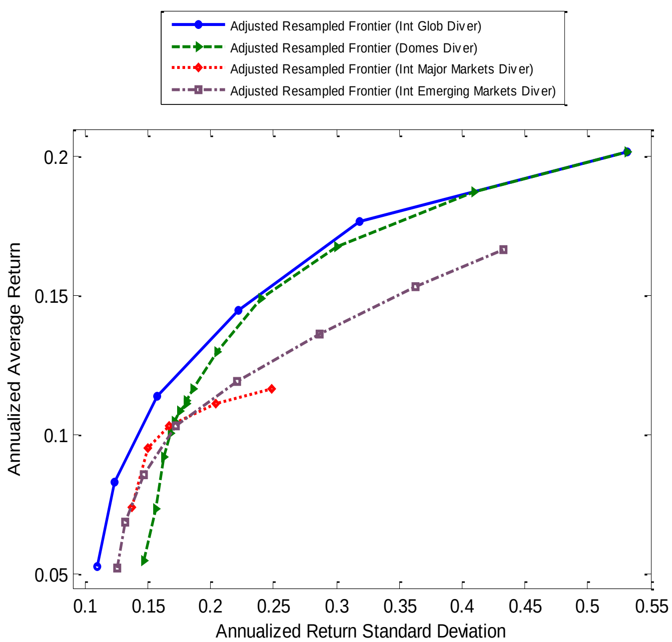

Figure 3. Resampled-Adjusted efficient frontiers of various resampled diversification strategies.

Figure 3 shows that the efficient diversification strategies are not obvious because the efficient frontiers intersect, revealing that regions of the dominance are ambiguous. With the exception of IND, it is not easy to determine which of the other three strategies will dominate each other. In this fact, Figure 3 shows that, for a risk level lower than 17.15 percent, the global diversification strategy dominates all the other strategies in the resampling approach. But, for the rest of risk levels, it is not easy to determine any superiority relationship among the different strategies. U.S. investors, who seek advice on investing internationally or domestically, could not be able to make a decision to choose any diversification strategy based on the improved–adjusted-resampled frontiers. Consequently, the optimal choice could not be made.

Stochastic Dominance results: Since the results obtained from the MV portfolio optimization approach could not be used to draw any preference from any international or domestic diversification strategy, we turn to apply the SD approach by adopting the non-parametric SD based on the MC and bootstrapped p-values simulation models developed by Barrett and Donald (BD, 2003) to examine the preference between DOD, IND, IMP, and IED portfolios. All SD tests conducted are based on both hypotheses stated, dominance or no dominance. Firstly, we summarize the results of the empirical dominance relationships between DOD and IND in Table 1 according to Property 1[iii].

We depict in Table 1 the summary of the BD test statistics on the dominance relationships of the pair-wise comparison of the 14 DODs and the 6 INDs. From the Table 1, we find that in general one could not conclude that American investors will always prefer DOD to IND or vice versa because the table shows the dominance relationships from both directions. To specify, Panel A of Table 1 shows that, in 26 percent of the cases, the p-values generated are statistically non-significant since they are higher than the critical p-value. For the DOD characterized by risk/return levels lower to 30 percent and 16.78 percent, respectively, we accept H_{0j}^{1} but we reject H_{0j}^{2}, showing that proposition (a) is confirmed. In 73 percent and 27 percent of cases, DOD portfolios first and second orders stochastically dominate (FSD and SSD) IND resampled efficient portfolios, respectively. In fact, local diversification stochastically dominates international diversification strategy. U.S. investor having a high risk-aversion coefficient prefers domestic market investment strategy. Home bias phenomenon is confirmed implying the acceptance of $H_{0}^{1'}$ hypothesis.

Panel B of the table 1 reveals that, in contrast to the panel A, in 73 percent of cases, IND dominates stochastically all the DOD. FSD and SSD relationships are appeared in 98 percent and 2 percent of cases, respectively, involving the acceptance of H_{0j}^{2} and the reject of H_{0j}^{1} hypothesis.

Table 1. Pair-wise results of the Stochastic dominance tests between DOD and IND.

Panel A		IND 1 [5.25%;10.91%]	IND 2 [8.30%; 12.30%]	IND 3 [11.40%; 15.76%]	IND 4 [14.48%; 22.21%]	IND 5 [17.68%; 31.86%]	IND 6 [20.18%; 53.13%]	Total	FS	SS
DOD 1 [5.46%; 14.62%]		ND	ND	ND	ND	FSD	FSD	2	2	0
DOD 2 [7.32%; 15.66%]		ND	ND	ND	ND	SSD	FSD	2	1	1
DOD 3 [9.23%; 16.28%]		ND	ND	ND	ND	FSD	FSD	2	2	0
DOD 4 [10.08%; 16.74%]		ND	ND	ND	ND	SSD	FSD	2	1	1
DOD 5 [10.49%; 17.15%]		ND	ND	ND	FSD	FSD	FSD	3	3	0
DOD 6 [10.88%; 17.58%]		ND	ND	ND	ND	FSD	FSD	2	2	0
DOD 7 [11.11%; 18.06%]		ND	ND	ND	ND	SSD	FSD	2	1	1
DOD 8 [11.25%; 18.09%]		ND	ND	ND	ND	FSD	FSD	2	2	0
DOD 9[11.64%; 18.57%]		ND	ND	ND	ND	SSD	FSD	2	1	1
DOD 10 [12.99%; 20.54%]		ND	ND	ND	ND	ND	FSD	1	1	0
DOD 11 [14.90%; 23.98%]		ND	ND	ND	ND	ND	SSD	1	0	1
DOD 12 [16.78%; 30.00%]		ND	ND	ND	ND	ND	SSD	1	0	1
DOD 13 [18.72%; 40.94%]		ND	ND	ND	ND	ND	ND	0	0	0
DOD 14 [20.18%; 53.13%]		ND	ND	ND	ND	ND	ND	0	0	0
					Panel B					
DOD 1 [5.46%; 14.62%]		ND	FSD	FSD	FSD	ND	ND			
DOD 2 [7.32%; 15.66%]		FSD	FSD	FSD	FSD	ND	ND			
DOD 3 [9.23%; 16.28%]		FSD	FSD	FSD	FSD	ND	ND			
DOD 4 [10.08%; 16.74%]		FSD	FSD	FSD	FSD	ND	ND			
DOD 5 [10.49%; 17.15%]		FSD	FSD	FSD	ND	ND	ND			
DOD 6 [10.88%; 17.58%]		FSD	FSD	FSD	FSD	ND	ND			
DOD 7 [11.11%; 18.06%]		FSD	FSD	FSD	FSD	ND	ND			
DOD 8 [11.25%; 18.09%]		FSD	FSD	FSD	FSD	ND	ND			
DOD 9 [11.64%; 18.57%]		FSD	FSD	FSD	FSD	ND	ND			
DOD 10 [12.99%; 20.54%]		FSD	FSD	FSD	FSD	ND	ND			
DOD 11 [14.90%; 23.98%]		FSD	FSD	FSD	FSD	FSD	ND			
DOD 12 [16.78%; 30.00%]		FSD	FSD	FSD	FSD	FSD	SSD			
DOD 13 [18.72%; 40.94%]		FSD	FSD	FSD	FSD	FSD	FSD			
DOD 14 [20.18%; 53.13%]		FSD	FSD	FSD	FSD	FSD	FSD			
Dominates	Total	13	14	14	13	4	3			
	FSD	13	14	14	13	4	2			
	SSD	0	0	0	0	0	1			

This table reports stochastic dominance relationships between domestic diversified (DOD) portfolios and international diversified (IND) portfolios in the sense of the *j* order stochastic dominance for *j*=1,2,3. The test is based on p-values simulation methods results of Barrett and Donald (2003) for the three SD orders (FSD, SSD and TSD). The results in the panel A are read based on rows-versus-column basis. For example, the first row and the seventh column tells us that DOD1 stochastically dominates IND6 in the sense of FSD. The results in the panel B are read based on column-versus-rows basis. For example, the first row and the seventh column tells us that IND6 does not stochastically dominate DOD. Values in brackets are mean and variance returns in percent, respectively.

The result infers that international diversification dominates stochastically domestic diversification strategy since proposition (b) is verified. U.S. investor affects 73 of his wealth abroad confirming the acceptance of the alternative hypothesis.

Besides, in majority of the cases, the p-values regrouped in panels A and B of the table 1 document the absence of SD relationship between the DOD and IND portfolios. More specifically, in 74 percent and 27 percent of cases, for the two sets of SD tests (DOD/IND and IND/DOD, respectively), the p-values are statistically significant (at the 5% level), implying the reject of both H_{0j}^{1} and H_{0j}^{2}. This leads us conclude that F and G do not dominate each other and their distributions may not be the same. Moreover, although the p-values seem to be statistically non-significant, in 4 percent of cases, the empirical results show that both H_{0j}^{1} and H_{0j}^{2} hypotheses are accepted infers no dominance between the strategies, which, in turn, reveals the indifference between these two strategies stated in the corresponding hypothesis.

Further, table 1 results suggest that the IND 2 and 3 are the most favorable portfolios and the DOD 13 and 14 are the least favorable portfolios as the former dominate 14 other portfolios at first order but aren't dominated by any other portfolios whereas the latter are dominated by all the 6 international diversified portfolios at first order but don't dominate any other portfolios. In term of the SD relationships frequency, the simultaneous analysis of the two panel's results reveals that a risk-adverse American investor having increasing utility function prefers the global international to the domestic diversification. The SD relationships between the DOD and IMP derived from BD (2003) simulated p-values are summarized in table 2.

Panel A of the table 2 suggests that the DOD seem to get better performance than the IMP portfolios. In 77 percent of the cases, the DOD stochastically dominate the IMP leading to the acceptance of H_{0j}^{1} and the reject H_{0j}^{2} hypothesis. More precisely, in 98 percent and 2 percent of cases, the DOD FSD and SSD the IMP, respectively. The SD tests of the DOD 1-10 to all the IMP show that p-values, generated either through KSB1, KSB2 or KSB3, are statistically non-significant implying the acceptance of the null hypothesis. For the risk/return levels lower to 23.98 percent and 14.9 percent, respectively, risk-adverse U.S. investor having increasing utility function prefers domestic diversification. Hence, the results confirm the acceptance of the $H_{0}^{1'}$ hypothesis.

The inverse dominance test, resumed in panel B of the table 2, shows that, only in 17 percent of cases, simulated p-values are statistically not significant implying the acceptance of H_{0j}^{2} and the reject of H_{0j}^{1} hypothesis. The IMP FSD and SSD the DOD, respectively, in 92 percent and 8 percent of cases. In this fact, U.S. risk-adverse investor involves in average of 17 percent of his wealth in international major markets for risk/return levels higher to 30 percent and 16.78 percent, respectively.

Further, the two dominance tests between DOD/IMP and IMP/DOD reported in panels A and B of the table 2 note the absence of dominance relationships in 23 percent and 83 percent of cases, respectively, H_{0j}^{1} and H_{0j}^{2} hypotheses are rejected. However, both hypotheses are simultaneously accepted in 4 percent of cases revealing the indifference between the two diversification strategies.

Referring to the SD relationships frequency, the results of the table 2 reveal that the DOD 1-10 are the most favorable portfolios and the DOD 13 and 14 are the least favorable portfolios as the former dominate all the 5 IMP at the first order but aren't dominated by any other portfolios whereas the latter are dominated by all the 5 IMP at first order but don't dominate any DOD portfolios. In conclusion, the pair-wise SD comparisons prove that the domestic diversification seems to be more beneficial than the international major markets diversification strategy since 77 percent of the American investor wealth' are invested locally. The pair-wise comparisons of the SD tests between the DOD and IED based on the simulated p-value are summarized in panels A and B of the table 3.

Panel A of the table 3 exhibits that the majority of the p-values generated from the two simulation procedures are statistically non-significant. In fact, in 82 percent of cases, the SD tests show that the DOD outperforms the IED. H_{0j}^{1} hypothesis is accepted and H_{0j}^{2} hypothesis is rejected. In 99 percent of cases, the DOD 1-11 FSD all the IED. For a risk levels lower to 30 percent, the U.S. investor having an increasing utility function prefers domestic to emerging markets diversification strategy.

Table 2. Pair-wise results of the Stochastic dominance tests between DOD and IMP.

Panel A	IMP 1 [7.39%; 13.72%]	IMP 2 [9.54%; 14.93%]	IMP 3 [10.32%; 16.70%]	IMP 4 [11.11%; 20.44%]	IMP 5 [11.63%; 24.80%]	Dominates		
DOD 1 [5.46%; 14.62%]	FSD	FSD	FSD	FSD	FSD	5	5	0
DOD 2 [7.32%; 15.66%]	FSD	FSD	FSD	FSD	FSD	5	5	0
DOD 3 [9.23%; 16.28%]	FSD	FSD	FSD	FSD	FSD	5	5	0
DOD 4 [10.08%; 16.74%]	FSD	FSD	FSD	FSD	FSD	5	5	0
DOD 5 [10.49%; 17.15%]	FSD	FSD	FSD	FSD	FSD	5	5	0
DOD 6 [10.88%; 17.58%]	FSD	FSD	FSD	FSD	FSD	5	5	0
DOD 7 [11.11%; 18.06%]	FSD	FSD	FSD	FSD	FSD	5	5	0
DOD 8 [11.25%; 18.09%]	FSD	FSD	FSD	FSD	FSD	5	5	0
DOD 9 [11.64%; 18.57%]	FSD	FSD	FSD	FSD	FSD	5	5	0
DOD 10 [12.99%; 20.54%]	FSD	FSD	FSD	FSD	FSD	5	5	0
DOD 11 [14.90%; 23.98%]	ND	FSD	FSD	FSD	FSD	4	4	0
DOD 12 [16.78%; 30.00%]	ND	ND	ND	ND	ND	0	0	0
DOD 13 [18.72%; 40.94%]	ND	ND	ND	ND	ND	0	0	0
DOD 14 [20.18%; 53.13%]	ND	ND	ND	ND	ND	0	0	0
Panel B								
DOD 1 [5.46%; 14.62%]	ND	ND	ND	ND	ND			
DOD 2 [7.32%; 15.66%]	ND	ND	ND	ND	ND			
DOD 3 [9.23%; 16.28%]	ND	ND	ND	ND	ND			
DOD 4 [10.08%; 16.74%]	ND	ND	ND	ND	ND			
DOD 5 [10.49%; 17.15%]	ND	ND	ND	ND	ND			
DOD 6 [10.88%; 17.58%]	ND	ND	ND	ND	ND			
DOD 7 [11.11%; 18.06%]	ND	ND	ND	ND	ND			
DOD 8 [11.25%; 18.09%]	ND	ND	ND	ND	ND			
DOD 9 [11.64%; 18.57%]	ND	ND	ND	ND	ND			
DOD 10 [12.99%; 20.54%]	ND	ND	ND	ND	ND			
DOD 11 [14.90%; 23.98%]	ND	ND	ND	ND	ND			
DOD 12 [16.78%; 30.00%]	FSD	SSD	ND	ND	ND			
DOD 13 [18.72%; 40.94%]	FSD	FSD	FSD	FSD	FSD			
DOD 14 [20.18%; 53.13%]	FSD	FSD	FSD	FSD	FSD			
Dominates: Total	3	3	2	2	2			
FSD	3	2	2	2	2			
SSD	0	1	0	0	0			

This table reports stochastic dominance relationships to test whether domestic diversified (DOD) portfolios dominate (strictly) international major markets diversified (IMP) portfolios and inversely in the sense of the j order stochastic dominance for j=1,2,3. The test is based on p-values simulation methods results of Barrett and Donald (2003) for the three SD orders (FSD, SSD and TSD). The results in the panel A are read based on rows-versus-column basis. The results in the panel B are read based on column-versus-rows basis. Values in brackets are mean and variance returns in percent, respectively.

Table 3. Pair-wise results of the Stochastic dominance tests between DOD and IED.

Panel A		IED 1 [5.22%; 12.51%]	IED 2 [6.85%; 13.13%]	IED 3 [8.56%; 14.70%]	IED 4 [10.33%; 17.17%]	IED 5 [11.94%; 22.06%]	IED 6 [13.62%; 28.62%]	IED 7 [15.33%; 36.33%]	IED 8 [16.68%; 43.26%]	Total	FSD	SSD
DOD 1 [5.46%; 14.62%]		FSD	FSD	FSD	FSD	FSD	FSD	FSD	FSD	8	8	0
DOD 2 [7.32%; 15.66%]		FSD	FSD	FSD	FSD	FSD	FSD	FSD	FSD	8	8	0
DOD 3 [9.23%; 16.28%]		FSD	FSD	FSD	FSD	FSD	FSD	FSD	FSD	8	8	0
DOD 4 [10.08%; 16.74%]		FSD	FSD	FSD	FSD	FSD	FSD	FSD	FSD	8	8	0
DOD 5 [10.49%; 17.15%]		FSD	FSD	FSD	FSD	FSD	FSD	FSD	FSD	8	8	0
DOD 6 [10.88%; 17.58%]		FSD	FSD	FSD	FSD	FSD	FSD	FSD	FSD	8	8	0
DOD 7 [11.11%; 18.06%]		FSD	FSD	FSD	FSD	FSD	FSD	FSD	FSD	8	8	0
DOD 8 [11.25%; 18.09%]		FSD	FSD	FSD	FSD	FSD	FSD	FSD	FSD	8	8	0
DOD 9 [11.64%; 18.57%]		FSD	FSD	FSD	FSD	FSD	FSD	FSD	FSD	8	8	0
DOD 10 [12.99%; 20.54%]		FSD	FSD	FSD	FSD	FSD	FSD	FSD	FSD	8	8	0
DOD 11 [14.90%; 23.98%]		FSD	FSD	FSD	FSD	FSD	FSD	FSD	FSD	8	8	0
DOD 12 [16.78%; 30.00%]		ND	ND	ND	ND	SSD	FSD	FSD	FSD	4	3	1
DOD 13 [18.72%; 40.94%]		ND	ND	ND	ND	ND	ND	ND	ND	0	0	0
DOD 14 [20.18%; 53.13%]		ND	ND	ND	ND	ND	ND	ND	ND	0	0	0
Panel B												
DOD 1 [5.46%; 14.62%]		ND	ND	ND	ND	ND	ND	ND	ND			
DOD 2 [7.32%; 15.66%]		ND	ND	ND	ND	ND	ND	ND	ND			
DOD 3 [9.23%; 16.28%]		ND	ND	ND	ND	ND	ND	ND	ND			
DOD 4 [10.08%; 16.74%]		ND	ND	ND	ND	ND	ND	ND	ND			
DOD 5 [10.49%; 17.15%]		ND	ND	ND	ND	ND	ND	ND	ND			
DOD 6 [10.88%; 17.58%]		ND	ND	ND	ND	ND	ND	ND	ND			
DOD 7 [11.11%; 18.06%]		ND	ND	ND	ND	ND	ND	ND	ND			
DOD 8 [11.25%; 18.09%]		ND	ND	ND	ND	ND	ND	ND	ND			
DOD 9 [11.64%; 18.57%]		ND	ND	ND	ND	ND	ND	ND	ND			
DOD 10 [12.99%; 20.54%]		ND	ND	ND	ND	ND	ND	ND	ND			
DOD 11 [14.90%; 23.98%]		ND	ND	ND	ND	ND	ND	ND	ND			
DOD 12 [16.78%; 30.00%]		ND	ND	ND	ND	ND	ND	ND	ND			
DOD 13 [18.72%; 40.94%]		FSD	FSD	FSD	FSD	FSD	SSD	ND	ND			
DOD 14 [20.18%; 53.13%]		FSD	FSD	FSD	FSD	FSD	FSD	FSD	FSD			
Dominates	Total	2	2	2	2	2	2	1	1			
	FSD	2	2	2	2	2	1	1	1			
	SSD	0	0	0	0	0	1	0	0			

This table reports stochastic dominance relationships to test whether domestic diversified (DOD) portfolios dominate (strictly) international EMERGING markets diversified (IED) portfolios and inversely in the sense of the j order stochastic dominance for j=1,2,3. The test is based on p-values simulation methods results of Barrett and Donald (2003) for the three SD orders (FSD, SSD and TSD). The results in the panel A are read based on rows-versus-column basis. The results in the panel B are read based on column-versus-rows basis. Values in brackets are mean and variance returns in percent, respectively.

Panel B of the table 3 reveals the absence of the SD relationships between the IED and the DOD since p-values generated are weak and even equal to 0. In fact, in 87.5 percent of cases, H_{0j}^{1} and H_{0j}^{2} hypotheses are rejected. Practically, the dominance relationships appear only towards the DOD 13 and 14 characterized by the relatively high risk/return levels. Only in 12.5 percent of cases, we accept H_{0j}^{2} and we reject H_{0j}^{1} hypothesis involving the dominance of the IED to DOD. Indeed, 93 percent of dominance relationships generated are of FSD order. Therefore, for the domestic diversified portfolio risk levels' higher to 40.94 percent, the American investor having an increasing utility function prefers allocate the 12.5 percent of his wealth in emerging markets through the diversification strategy.

The results of the table 3 reveal that the DOD 1-11 are the most favorable portfolios and the DOD 14 is the least favorable portfolio as the former dominate all the 8 IED at the first order but aren't dominated by any other portfolios whereas the latter is dominated by all the 8 IED at first order but doesn't dominate any DOD portfolios. Analysis results report the advantage of the domestic diversification strategy for a risk levels lower to 30 percent in average. The SD test results between IND and IMP are reported in table 4.

The empirical results of the panel A of the table 4 show that global international diversification dominates entirely major markets diversification strategy. In 90 percent of cases, the IND 1-6 FSD the IMP 1-5. P-values generated from KSB1, KSB2 and KSB3 simulation methods are higher to 5 percent significance level involving the acceptance of H_{0j}^{3} and the reject of H_{0j}^{4} hypothesis. The IND 1-5 seem to be the more favorable portfolios since the former dominate all the 5 IMP but aren't dominated by any other portfolios.

Inversely, the findings of the panel B of the table 4 reveal that neither SD relationships of the IMP to the IND have been illustrated. In 93 percent of cases, the simulated p-values are statistically significant and lead to the reject of H_{0j}^{3} and H_{0j}^{4} hypotheses. Besides, in 7 percent of cases, the results of the panels A and B of the table 4 show that the indifference choice is displayed between the IND 6 and IMP 1 and 2 although the p-values are statistically non-significant. Since H_{0j}^{3} and H_{0j}^{4} are simultaneously accepted, we fail to conclude the dominance between the two resampled diversification strategies.

Through the period study considered, the U.S. risk-adverse investor who possesses an increasing utility function (confirming $H_{0}^{3'}$ hypothesis acceptance) prefers international global diversification and invests the 90 percent of his wealth abroad. Comparative analysis between IND and IED, based on BD (2003) test, is reported in table 5.

Panel A of the table 5 reveals that the IND portfolios dominate stochastically the IED. Indeed, in 100 percent of cases, the p-values generated from KSB1, KSB2 and KSB3 methods are statistically non-significant. However, only in 96 percent of cases, the IND FSD (in 96 percent of cases) and SSD (in 4 percent of cases) the IED, implying the acceptance of H_{0j}^{3} and the reject of H_{0j}^{4} hypothesis.

Referring to the frequency of the SD relationships, we find that the IND 1-5 are the most favorable portfolios as the former dominate all the 8 IED at the first order but aren't dominated by any other portfolios.

The inversely test, summarized in the panel B of the table 5, reveals that the IND outperform the IED. In 96 percent of the cases, the p-values generated from the simulation methods are statistically significant implying the absence of the SD relationships. Consequently, H_{0j}^{3} and H_{0j}^{4} hypotheses are rejected. The emerging markets diversification could not be able to beat the global international diversification. The American investor having an increasing utility function prefers to invest totally in the international global markets. $H_{0}^{3'}$ hypothesis is verified. The results of the pair-wise comparison between the IMP and IED are summarized in the panels A and B of the table 6. In 45 percent of cases, panel A of the table 6 notes the dominance of the IMP to the IED. More specifically, in 45 percent of cases, the IMP show FSD (in 94 percent of cases) and SSD (in 6 percent of cases) relationships toward the IED implying the acceptance of H_{0j}^{3} and the reject of H_{0j}^{4} hypothesis. The empirical findings reveal that the IMP 3 is the most favorable portfolio and the IED 6-8 are the least favorable portfolios as the former dominates the IED 3 (1) at the first (second) order but aren't dominated by any other portfolios whereas the latter are dominated by all the 6 IMP at first order but don't dominate any other portfolios.

Table 4. Pair-wise results of the Stochastic dominance tests between IND and IMP.

Panel A		IMP 1 [7.39%; 13.72%]	IMP 2 [9.54%; 14.93%]	IMP 3 [10.32%; 16.70%]	IMP 4 [11.11%; 20.44%]	IMP 5 [11.63%; 24.80%]	Total	FSD	SSD
IND 1 [5.25%; 10.91%]		FSD	FSD	FSD	FSD	FSD	5	0	
IND 2 [8.30%; 12.30%]		FSD	FSD	FSD	FSD	FSD	5	0	
IND 3 [11.40%; 15.76%]		FSD	FSD	FSD	FSD	FSD	5	0	
IND 4 [14.48%; 22.21%]		FSD	FSD	FSD	FSD	FSD	5	0	
IND 5 [17.68%; 31.86%]		FSD	FSD	FSD	FSD	FSD	5	0	
IND 6 [20.18%; 53.13%]		FSD	FSD	ND	ND	ND	2	0	
Panel B									
IND 1 [5.25%; 10.91%]		ND	ND	ND	ND	ND			
IND 2 [8.30%; 12.30%]		ND	ND	ND	ND	ND			
IND 3 [11.40%; 15.76%]		ND	ND	ND	ND	ND			
IND 4 [14.48%; 22.21%]		ND	ND	ND	ND	ND			
IND 5 [17.68%; 31.86%]		ND	ND	ND	ND	ND			
Dominates	Total	0	0	0	0	0			
	FSD	0	0	0	0	0			
	SSD	0	0	0	0	0			

This table reports stochastic dominance relationships to test whether international diversified (IND) portfolios dominate (strictly) international major markets diversified (IMP) portfolios and inversely in the sense of the j order stochastic dominance for j=1,2,3. The test is based on p-values simulation methods results of Barrett and Donald (2003) for the three SD orders (FSD, SSD and TSD). The results in the panel A are read based on rows-versus-column basis. The results in the panel B are read based on column-versus-rows basis. Values in brackets are mean and variance returns in percent, respectively.

Table 5. Pair-wise results of the Stochastic dominance tests between IND and IED.

Panel A	IED 1 [5.22%; 12.51%]	IED 2 [6.85%; 13.13%]	IED 3 [8.56%; 14.70%]	IED 4 [10.33%; 17.17%]	IED 5 [11.94%; 22.06%]	IED 6 [13.62%; 28.62%]	IED 7 [15.33%; 36.33%]	IED 8 [16.68%; 43.26%]	Total	FSD	SSD
IND 1 [5.25%; 10.91%]	FSD	FSD	FSD	FSD	FSD	FSD	FSD	FSD	8	8	0
IND 2 [8.30%; 12.30%]	FSD	FSD	FSD	FSD	FSD	FSD	FSD	FSD	8	8	0
IND 3 [11.40%; 15.76%]	FSD	FSD	FSD	FSD	FSD	FSD	FSD	FSD	8	8	0
IND 4 [14.48%; 22.21%]	FSD	FSD	FSD	FSD	FSD	FSD	FSD	FSD	8	8	0
IND 5 [17.68%; 31.86%]	FSD	FSD	FSD	FSD	FSD	FSD	FSD	FSD	8	8	0
IND 6 [20.18%; 53.13%]	ND	ND	SSD	SSD	FSD	FSD	FSD	FSD	6	4	2
Panel B											
IND 1 [5.25%; 10.91%]	ND	ND	ND	ND	ND	ND	ND	ND			
IND 2 [8.30%; 12.30%]	ND	ND	ND	ND	ND	ND	ND	ND			
IND 3 [11.40%; 15.76%]	ND		ND	ND	ND	ND	ND	ND			
IND 4 [14.48%; 22.21%]	ND	ND	ND	ND	ND	ND	ND	ND			

Continue…

IND 5 [17.68%; 31.86%]		ND	ND	ND	ND	ND	ND	ND	ND
IND 6 [20.18%; 53.13%]		ND	ND	ND	ND	ND	ND	ND	ND
Dominates	Total	0	0	0	0	0	0	0	0
	FSD	0	0	0	0	0	0	0	0
	SSD	0	0	0	0	0	0	0	0

This table reports stochastic dominance relationships to test whether international diversified (IND) portfolios dominate (strictly) international emerging markets diversified (IED) portfolios and inversely in the sense of the j order stochastic dominance for j=1,2,3. The test is based on p-values simulation methods results of Barrett and Donald (2003) for the three SD orders (FSD, SSD and TSD). The results in the panel A are read based on rows-versus-column basis. The results in the panel B are read based on column-versus-rows basis. Values in brackets are mean and variance returns in percent, respectively.

Table 6. Pair-wise results of the Stochastic dominance tests between IMP and IED.

Panel A		IED 1 [5.22%; 12.51%]	IED 2 [6.85%; 13.13%]	IED 3 [8.56%; 14.70%]	IED 4 [10.33%; 17.17%]	IED 5 [11.94%; 22.06%]	IED 6 [13.62%; 28.62%]	IED 7 [15.33%; 36.33%]	IED 8 [16.68%; 43.26%]	Total	FSD	SSD
IMP 1 [7.39%; 13.72%]		ND	ND	ND	ND	FSD	FSD	FSD	FSD	4	4	0
IMP 2 [9.54%; 14.93%]		ND	ND	ND	ND	FSD	FSD	FSD	FSD	4	4	0
IMP 3 [10.32%; 16.70%]		ND	ND	ND	ND	SSD	FSD	FSD	FSD	4	3	1
IMP 4 [11.11%; 20.44%]		ND	ND	ND	ND	ND	FSD	FSD	FSD	3	3	0
IMP 5 [11.63%; 24.80%]		ND	ND	ND	ND	ND	FSD	FSD	FSD	3	3	0
										4	4	0
Panel B												
IMP 1 [7.39%; 13.72%]		ND	ND	ND	ND	ND	ND	ND	ND			
IMP 2 [9.54%; 14.93%]		ND	ND	ND	ND	ND	ND	ND	ND			
IMP 3 [10.32%; 16.70%]		ND	ND	ND	ND	ND	ND	ND	ND			
IMP 4 [11.11%; 20.44%]		ND	SSD	ND	ND	ND	ND	ND	ND			
IMP 5 [11.63%; 24.80%]		SSD	FSD	ND	ND	ND	ND	ND	ND			
Dominates	Total	1	2	0	0	0	0	0	0			
	FSD	0	1	0	0	0	0	0	0			
	SSD	1	1	0	0	0	0	0	0			

This table reports stochastic dominance relationships to test whether international major markets diversified (IMP) portfolios dominate (strictly) international emerging markets diversified (IED) portfolios and inversely in the sense of the j order stochastic dominance for j=1,2,3. The test is based on p-values simulation methods results of Barrett and Donald (2003) for the three SD orders (FSD, SSD and TSD). The results in the panel A are read based on rows-versus-column basis. The results in the panel B are read based on column-versus-rows basis. Values in brackets are mean and variance returns in percent, respectively.

Nevertheless, in 52.5 percent of cases, the SD tests show that the two hypotheses H_{0j}^{3} and H_{0j}^{4} are accepted although the non-significance of the simulated p-values. The U.S. investor is indifferent between the major and emerging markets resampled diversification strategies.

Panel B of the table 6 reports, in 92.5 percent of cases, the absence of dominance relationships between the IED and IMP. Nevertheless, in 7.5 percent of cases, we accept the H_{0j}^{4} hypothesis and we reject the H_{0j}^{3} hypothesis inferring to the FSD (in 33 percent of cases) and the SSD (in 67 percent of cases) relationships of the IED to the IMP resampled portfolios. Similarly to the panel A results, in 47.5 percent of cases, the panel B findings reveal that the American investor seems to be indifferent between the IED 1-5 and IMP 1-5 portfolios.

H_{0j}^3 and H_{0j}^4 hypotheses are simultaneously accepted. If we summarize the findings of the SD tests, the risk-adverse U.S. investor having an increasing utility function prefers to diversify 45 percent of his wealth in major markets.

CONCLUSION

In this paper, we investigate the impact of the estimation errors on the financial portfolios optimization processes and we apply the nonparametric SD approach based on the stochastic test statistics' and the simulated p-values using the MC and bootstrap methods to resolve the problem of the domestic and international diversification strategy choices for an American investor view of point.

Basing on the daily quotations of American, Latin American, Asian financial block index markets and American stocks for the period from 1993 to 2007, the empirical results show that the estimation errors consideration in input parameters imply the large changes in the optimized portfolio composition and the considerably modification of the MV efficient frontiers shape. Since the MV optimization could not be used to draw any preference between the international and domestic diversification, the results reveal the usefulness of the SD approach to define the optimal choice.

Besides, we find that the international global diversification enhances the feasibility of the optimal strategies indeed the benefits of the local diversification even though the global financial market integrations. For the risk levels higher to 30 percent, in 73 percent of cases, the risk-adverse American investor having an increasing utility function prefers the global international to the domestic resampled diversification. According to the degree of the p-values SD tests statistical significance', the empirical findings show that an American investor having a high risk-aversion coefficient, for the risk levels lower to 30 percent and 23.98, respectively, prefers the domestic to the international major and emerging markets diversification. The pair-wise SD comparisons reveal that the domestic diversification seems to be more beneficial than the international major and emerging markets diversification strategies as 77 percent and 82 percent respectively, of the American investor wealth' are invested locally. Further, the SD tests report that the global international diversification dominates entirely the major and emerging markets diversification strategies for the U.S. risk-adverse investor having an increasing utility function. Finally, the findings of the SD tests suggest that the risk-adverse U.S. investor having an increasing utility function prefers to diversify 45 percent of his wealth in the major markets rather than in the emerging markets.

It should be noted that the MV approach used in the paper have a limitation because its inference may not be valid when the date are far away from normally distribution. One may consider applying other techniques, such as CAPM statistics (Leung and Wong, 2008), Value-at-Risk (VaR) and CVaR (Ma and Wong, 2010) for selecting investment positions. We note that the conclusions drawn from the SD and MV results in the paper are consistent. In addition, the conclusion drawn from SD is equivalent to many other non-normal approaches. For example, it is well known that the finding from FSD is equivalent to that from VaR, and the finding from SSD is equivalent to that from CVaR, readers may refer to Ma and Wong (2010) and the references therein for more information.

Our paper only examines the preferences of risk averters, extension could include examination of preferences for other types of investors, for example, investors with S-shaped and reverse S-shaped utility functions, see, for example, Wong and Ma (2008) and Broll et al. (2010) for more discussion. Investors could also apply other techniques, for example, portfolio optimization (Bai et al. 2009a,b, 2011b; Egozcue and Wong, 2010; Egozcue et al. 2011). One may apply other theories, for example, behavioral finance (Lam et al., 2010, 2012) to examine the behaviors of different investors.

REFERENCES

Abhyankar, A., Ho, K., and Zhao, H. (2009). International Value versus Growth: Evidence from Stochastic Dominance Analysis. *International Journal of Finance and Economics*, 14, 222-232.

Abid, F., Mroua, M. and Wong, W.K.. (2009). The Impact of Option Strategies in Financial Portfolios Performance: Mean-Variance and Stochastic Dominance Approaches. *Finance India*, 23, 503-526.

Abid, F., Mroua, M. and Wong, W.K. (2013). Should Americans Invest Internationally? The Mean-Variance Portfolios Optimization and stochastic dominance approaches. *Risk and Decision Analysis*, 4, 89-102.

Abu Mansor, S.N., Baharum, A. and Kamil, A.A. (2006). Portfolio Resampling in Malaysian Equity Market. *Monte Carlo Methods and Applications*, 12, 261-269.

Anderson, G. (1996). Nonparametric Tests of Stochastic Dominance in Income Distributions. *Econometrica*, 64, 1183-1193.

Anderson, G. (2004). Toward an empirical analysis of polarization. *Journal of Econometrics*, 122, 1-26.

Antoniou, A., Olusi, O. and Paudyal, K. (2010). Equity Home-Bias: A Suboptimal Choice for UK investors?. *European Financial Management*, 16, 449-479.

Bai, Z.D., Li, H., Liu, H.X. and Wong, W.K. (2011a). Test Statistics for Prospect and Markowitz Stochastic Dominances with Applications. *Econometrics Journal*, 14, 278-303.

Bai, Z.D., Liu, H.X. and Wong, W.K. (2009a). Enhancement of the Applicability of Markowitz's Portfolio Optimization by Utilizing Random Matrix Theory. *Mathematical Finance*, 19, 639-667.

Bai, Z.D., Liu, H.X. and Wong, W.K. (2009b). On the Markowitz Mean-Variance Analysis of Self-Financing Portfolios. *Risk and Decision Analysis*, 1, 35-42.

Bai, Z.D., Liu, H.X. and Wong, W.K. (2011b). Asymptotic Properties of Eigenmatrices of A Large Sample Covariance Matrix. *Annals of Applied Probability*, 21, 1994-2015.

Bai, Z.D., Wang, K.Y. and Wong, W.K. (2011b). Mean-Variance Ratio Test, A Complement to Coefficient of Variation Test and Sharpe Ratio Test. *Statistics and Probability Letters*, 81, 1078-1085.

Barrett, G. and Donald, S. (2003). Consistent tests for stochastic dominance. *Econometrica*, 71, 71-104.

Becker, F., Gürtler, M. and Hibbeln, M. (2009). Markowitz versus Michaud: Portfolio Optimization Strategies Reconsidered. Working Paper SSRN.

Best, J.M. and Grauer, R. (1991). Sensitivity Analysis for Mean-Variance Portfolio Problems. *Management Science*, 37, 980-989.

Broll, U., Egozcue, M., Wong, W.K. and Zitikis, R. (2010). Prospect Theory, Indifference Curves, and Hedging Risks. *Applied Mathematics Research Express*, 2, 142–153.

Broll, U., Wahl, J.E. and Wong, W.K. (2006). Elasticity of Risk Aversion and International Trade. *Economics Letters*, 92, 126-130.

Ceria, S. and Stubbs, R. (2006). Incorporating estimation errors into portfolio selection: Robust portfolio construction. *Journal of Asset Managemen*t, 7, 109-127.

Chiou, W.P. (2008) .Who benefits more from international diversification?. *Institutions and Money*, 18, 466-482.

Chiou, W.P. (2009). Benefits of international diversification with investment constraints: An over-time perspective. *Journal of Multinational Financial Management*, 19, 93-110.

Chopra, V.K. and Ziemba, W.T. (1993). The effect of errors in means, variances, and covariances on optimal portfolio choice. *The Journal of Portfolio Management*, 19, 6-11.

Davidson, R. and Duclos, J.Y. (2000). Statistical Inference for the measurement of the incidence of taxes and transfers. *Econometric*a, 52, 761-776.

Driessen, J. and Laeven, L. (2007). International Portfolio Diversification Benefits: Cross-Country Evidence from a Local Perspective. *Journal of Banking and Finance*, 31, 1693-1712.

Egozcue, M. and Wong, W.K. (2010). Gains from Diversification on Convex Combinations: A Majorization and Stochastic Dominance Approach. *European Journal of Operational Research*, 200, 893–900.

Egozcue, M., García, L.F., Wong, W.K. and Zitikis, R. (2011). Do Investors like to Diversify? A Study of Markowitz Preferences. *European Journal of Operational Research*, 215, 188-193.

Fabozzi, F., Kolm, P., Pachamanova, D. and Focardi, S. (2007). Robust portfolio optimization and management. John Wiley & Sons Inc edition.

Fletcher, J. and Hillier J. (2001). An Examination of Resampled Portfolio Efficiency. *Financial Analysts Journal*, September/October, 66-74.

Fong, W.M., Wong, W.K. and Lean, H.H. (2005). International Momentum Strategies: A Stochastic Dominance Approach. *Journal of Financial Markets*, 8, 89–109.

Fong, W.M., Lean, H.H. and Wong, W.K. (2008). Stochastic Dominance and Behavior towards Risk: The Market for Internet Stocks. *Journal of Economic Behavior and Organization*, 68, 194-208.

French, K. and Poterba, J. (1991). Investor Diversification and International Equity Markets. *American*

Economic Review, 81, 222-226.

Hadar, J. and Russel, R. (1969). Rules for ordering uncertain prospects. *American Economic Review*, 59, 25-34.

Hanoch, G. and Levy, H. (1969). The Efficiency Analysis of Choices Involving Risk. *Review of Economic Studies*, 36, 335-346.

Jobson, J.D. and Korkie, B. (1980). Estimation of Markowitz efficient portfolios. *Journal of the American Statistical Association*, 75, 544–554.

Jobson, J.D. and Korkie, B. (1981). Putting Markowitz Theory to Work. *Journal of Portfolio Management*, 70-74.

Lam, K., Liu, T. and Wong, W.K. (2010). A pseudo-Bayesian model in financial decision making with implications to market volatility, under- and overreaction. *European Journal of Operational Research*, 203, 166-175.

Lam, K., Liu, T. and Wong, W.K. (2012). A New Pseudo Bayesian Model with Implications to Financial Anomalies and Investors' Behaviors. *Journal of Behavioral Finance*, 13, 93-107.

Lean, H.H., McAleer, M. and Wong, W.K. (2010). Market Efficiency of Oil Spot and Futures: A Mean-Variance and Stochastic Dominance Approach. *Energy Economics*, 32, 979–986.

Lean, H.H., Smyth, R. and Wong, W.K. (2007). Revisiting Calendar Anomalies in Asian Stock Markets Using a Stochastic Dominance Approach. *Journal of Multinational Financial Management*, 17, 125–141.

Leung, P.L. and Wong, W.K. (2008). On testing the equality of the multiple Sharpe ratios, with application on the evaluation of IShares. *Journal of Risk*, 10, 1-16.

Li, K., Sarkar, A. and Wang, Z. (2003). Diversification Benefits of Emerging Markets Subject to Portfolio Constraints. *Journal of Empirical Finance*, 10, 57-80.

Ma, C. and Wong, W.K. (2010). Stochastic Dominance and Risk Measure: A Decision-Theoretic Foundation for VaR and C-VaR. *European Journal of Operational Research*, 207, 927–935.

Markowitz, H. (1952). Portfolio selection. *Journal of Finance*, 7, 77-91.

Markowitz, H. (1959). Portfolio selection: Efficient Diversification of Investment. New Haven, Yale University Press.

Markowitz, H. and Usmen, N. (2003). Resampled Frontiers versus Diffuse Bayes: An Experiment. *Journal of Investment Management*, 1, 9-25.

Meyer, T.O. and Rose, L.C. (2003). The persistence of international diversification benefits before and during the Asian crisis. *Global Finance Journal*, 14, 217-242.

Michaud, R.O. (1998). Efficient Asset Management. Harvard Business School: Boston.

Michaud R. O. and Michaud R. O. (2008). Estimation Error and Portfolio Optimization: A Resampling Approach. *Journal of Investment Management*, 6, 8-28.

Porter, R. B. and Gaumnitz, J. E. (1972). Stochastic dominance vs. mean-variance analysis: An empirical evaluation. *American Economic Review*, 62, 438-446.

Rose, C., Meyer, O. and Li, M. (2005). Comparing mean variance with stochastic dominance tests when assessing international portfolio diversification benefits. *Financial Services Review*, 14, 149-168.

Rothschild, M. and Stiglitz, J.E. (1970). Increasing risk: A definition. *Journal of Economic Theory*, 2, 225-243.

Scherer, B. (2002). Portfolio Resampling: Review and Critique. *Financial Analysts Journal*, 98-109.

Scherer, B. (2004). Resampled efficiency and portfolio choice. *Financial Markets and Portfolios Management*, 18, 382-398.

Solnik, B. (1995). Why not diversify internationally rather than domestically?. *Financial Analysts Journal,* January/February, 89-94

Sriboonchitta, S., Wong, W.K., Dhompongsa, S. and Nguyen, H. T. (2009). Stochastic dominance and applications to finance, risk and economics. Chapman and Hall/CRC, Taylor and Francis Group, Boca Raton: Florida, USA.

Tesar, L. and Werner, I. (1995). Home bias and high turnover. *Journal of International Money & Finance*, 14, 467-492.

Wong, W.K. (2007). Stochastic dominance and mean-variance measures of profit and loss for business planning and investment. *European Journal of Operational Research*, 182, 829-843.

Wong, W.K. and Ma, C. (2008), 'Preferences over location-scale family', *Economic Theory*, 37, 119-146.

Wong, W.K., Phoon, K.F. and Lean, H.H. (2008). Stochastic dominance analysis of Asian hedge funds. *Pacific-Basin Finance Journal*, 16, 204-223.

Wong, W.K., Thompson, H.E., Wei, S. and Chow, Y.F. (2006). Do Winners perform better than Losers? A Stochastic Dominance Approach. *Advances in Quantitative Analysis of Finance and Accounting*, 4, 219-254.

Footnotes.

[i] Abitibi-Consolidated Inc (ABY), American Electric Power Co Inc (AEP), American Express Co (AXP), Apple Computer Inc (AAPL), Bank of New York (BK), Coca-Cola Co (KO), Computer Associates International Inc (CA), Delta Air Lines Inc (DAL), Exxon Mobil Corp (XOM), General Electric Co (GE), General Motors Corp (GM), International Business Machines Corp (IBM), Lockheed Martin Corp (LMT), Oracle Corp (ORCL), Royal Dutch Petroleum Company (RD), Southwest Airlines Inc (LUV), Motorola Inc (MOT), AMR Corp (AMR), Bank of America Corp (BAC), Ford Motor Co (F), American International Group Inc (AIG), Bristol-Myers Squibb Co (BMY), Burlington Northern Santa Fe Corp (BNI), CH Energy Group Inc (CHG), Citigroup Inc (C), DTE Energy Co (DTE), Fedex Corp (Federal Express) (FDX), Intel Corp (INTC), McDonald's Corp (MCD), and Russell Corp (RML).

[ii] The SD theory could be extended further to satisfy non-expected utilities, see, for example, Wong and Ma (2008) and the references contained therein for more information.

[iii] We note that the SD relationships based on the MC simulation draw the same conclusions as those drawn from the bootstrap simulation method. Thus, we only display SD relationships based on the MC simulation.