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International Portfolio Diversification Benefits: The Relevance of Emerging Markets

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Abstract

This paper studies the international portfolio diversification benefits in equity investing from the perspective of an American investor in a context of a growing market correlation. Different investment strategies employing different risk measures (standard variance, GARCH variance, CVaR, LPM (n)) are used to assess the robustness of international diversification benefits. Equity returns from 41 countries are used, including developed, emerging and frontier markets, during the period from 1988–2009.

Our empirical results show that economic gains from international equity diversification are still substantial despite the growing market correlations. Interestingly, international equity diversification allows obvious reduction of returns variability and minimum loss, and this only for restricted portfolios.

We found also that emerging markets continue to be an important component of well-diversified portfolios. A substantial investment in emerging and frontier markets enhances the economic gains of diversified portfolios while it does not seem to reduce portfolio returns variability and minimum loss. However, they consistently improve the risk –based performance measured by the semi variability ratio when we decrease their component in a well diversified portfolio.

Keywords: international, portfolio, diversification, emerging markets, risk measures

1. Introduction

A key issue in asset allocation and risk management is whether international diversification benefits is still substantial in the context of growing stock market correlation and crises occurrence, due to economic and financial integration. This topic attracted considerable attention during these last decades, since lower correlation between stocks is generally associated with higher diversification benefits, (see, for example, Meric & Meric, 1997; Divecha et al., 1992; Michaud et al., 1996; DeFusco et al., 1996). An interesting question arises as to whether international equity diversification benefits still exist just when they are most needed.

Although the benefit of international equity diversification has been extensively studied, there is not a definitive conclusion about the relevance of well diversified equity portfolio in the new international context. Li et al. (2003) showed that even as international markets are becoming more integrated, it does not eliminate the diversification benefits of investment in emerging markets. Das and Uppal (2004) studied international asset allocation in the presence of a systemic (perfectly correlated) risk, and found that they decrease (albeit only slightly) the gains from international diversification. Driessen and Laeven (2007) found that diversification benefits have decreased for most countries over the past two decades. Unexpectedly, Chue (2005) found that the international diversification benefits can rise (rather than fall) in states when the international stock returns correlations are high. Chiou (2009) suggested that international diversification benefits the U.S. local investor even with investment constraints, such as short-sale and overweighting, and even with the increasing integration of global financial markets.

Moreover, the existing empirical work on diversification benefits typically emphasizes on simple investment strategies and/or on few risk-based optimization approaches. Indeed, empirical studies report that different risk measures do not generate the same portfolios in case of non normal distribution of financial series. Thus, research performed by Markowitz (1959) has shown that, in case of normal distribution, both variance and downside risk measures provide the correct answer. However, when returns distribution is non normal, only the downside risk measures do. This idea has been supported later by Artzner et al. (1999), Rockafellar and Uryasev (2002), Ho et al. (2008), Cain and Zurbruegg (2010). As empirical literature highlights non normal characteristics in financial asset returns, such as Leptokurtosis and Skewness, (see, for example, Bali, 2003; Longin, 1996), we think that the study of international diversification benefits occurrence whatever the risk measure used in the optimization portfolio problem is a promising field. Our research should provide robust results about the relevance of international portfolio diversification. To our knowledge, this study has been the first attempt to employ various risk based optimization portfolios in an international diversification context; although a related study undertaken by Lagoarde-Segot and Lucey (2007) has used five optimization models to study the portfolio diversification benefits, it focused only on the Middle East and North Africa (Morocco, Tunisia, Egypt, Jordan, Lebanon, Turkey and Israel).

Furthermore, many studies focus on the attractiveness of emerging markets in international portfolio diversification as a substitution to developed ones; this interest is motivated by their portfolio risk reduction due to the low correlation with developed markets, (see, for example, Speidell & Sappenfield, 1992; Errunza, 1977; Kohers et al.,1998; Harvey, 1995; Lagoarde-Segot & Lucey, 2007; Gupta & Donleavy, 2009). However, the growing economic and financial integration of emerging markets has put in check their attractiveness to an international investor. Indeed, emerging markets have been associated with volatility and turmoil. Divecha et al. (1992) have reported high returns and high volatility in emerging markets. Some recent studies highlight a lack of significant gains from diversifying in emerging markets; for instance, Bordo (2003) suggested that the series of crises that occurred in Asia and Latin America seem to offset the positive effect of financial markets liberalization in emerging markets. Others studies highlighted a decrease of the benefits of emerging markets: for example, using a 16-year sample from 1988 to 2003, Garza-Gómez and Metghalchi (2006) found that ex-post benefits to U.S. investors who invested in this period in emerging markets are small. Moreover, Christoffersen et al. (2012) showed that diversification benefits from adding emerging markets to a portfolio appear to be large compared to benefits of adding additional developed markets, even if they are getting smaller in an absolute sense. Thus, the pertinence of emerging markets in international portfolio diversification is an ongoing debate.

The aim of this paper is to investigate the portfolio international diversification benefits while using different risk measures in portfolio optimizations. Our focus is on the domestic U.S. investor. We use 41 monthly international indexes expressed in USD over the period of 29 January 1988–31 December 2009. To provide a more in-depth study, the 41 countries used in this study are divided into emerging and frontier markets (hereafter Emerg. markets) versus developed markets in accordance with the MSCI classification. In our paper, besides comparing internationally diversified portfolios to a domestic investment, we assess the relevance of emerging markets to an American investor.

The empirical part of this paper consists of three stages. In the first, descriptive statistics on stock returns were performed. Afterwards, different risk measures were employed in the construction of the portfolios; an equally weighted portfolio and a domestic portfolio were also used as benchmarks. Therefore economic and statistical performance measures were used to compare the investment strategies which were tested annually for 18 years. The 18-year period is used as it provides a comprehensive analysis of the international portfolio diversification benefits under different stock market conditions.

This paper is outlined as follows: Theoretical development is present in section 2. Section 3 presents method and the database. Results and discussion are presented in section 4. Finally, conclusions are summarized in section 5.

2. Theoretical Development

Different risk measures are used in the various studies such as the standard variance of Markowitz, time varying risk measures. For example, the extended GARCH variance (General Autoregressive Conditional Heteroskedasticity variance which is developed by Bollerslev, 1986), the downside risk measures, such as the lower partial moments (LPM), and the risk measures based on the quantile as VaR (Value at risk) and CVaR (Conditional value at risk). The extended GARCH variance takes into account the kurtosis in returns distribution. The lower partial moments, the VaR and the CVaR take into account the asymmetry in returns distribution. Each risk measure is employed to compute an optimal portfolio, by solving the following optimization problem:

Minimize 'risk' SC/

$$\sum_{i=1}^{n} x_i = 1 \text{; i: 1…41} \tag{1}$$

LB=< x_i <= UB; i: 1…41;

$\sum_{i=1}^{n} x_i * R_i$ >= minimum portfolio return.

Mean-risk optimization problem involves two possibilities, the first requires solving the maximum expected return for a given risk level. The second consists on minimizing risk for a given return. Above, we present the second as the investor is averse to risk. Thus, he tends to minimize portfolio risk while imposing a satisfactory level of return.

3. Method and Database

3.1 Method

Different investment strategies are established in the construction of portfolios using 41 monthly international indexes expressed in US dollar including developed, emerging and frontier markets over the period of 29 January 1988–31 December 2009. Each investment strategy differs in terms of what the risk measure is to be minimized. Computer programs have been developed for portfolio constructions; all the programs have been conducted using MATLAB. To avoid the problem of market reclassification through time, we set emerging and frontier markets in the same group (Note 1). Although there are varying definitions of what precisely is an emerging market, we referred to the MSCI market classification to set the boundary between developed versus emerging and frontier markets.

Then out-of-sample rolling windows are used to obtain 18 different non overlapping test periods. The first testing period and the last ones started respectively in January 1992 and January 2009. The following procedure is repeated 18 times: at iteration 1, the different optimization models (mean-variance, mean-GARCH variance, mean-CVaR95, mean-CVaR97, mean-LPM2, mean-LPM3, mean-LPM4, mean-LPM5) are built using observations 1 48 and evaluated on observations 49–60, at iteration 2 models are built using observations 13–60 and evaluated on observations 61–72, etc.

3.1.1 Investment Strategies

In this study, we focus on pure stock portfolios; our attention is devoted to the private investor who cannot short sell. We impose the short sell condition as (Ho et al., 2008; Moreno et al., 2005; Cain and Zurbruegg, 2010; Nawrocki, 1992; Rockefellar and Uryasev, 2000; Martin, 1955; Gupta and Donleavey, 2009). Eight portfolios issued from optimization problems have been considered. An equally weighted portfolio and a domestic one have also been employed as benchmarks to compare the benefit of international portfolio diversification provided by more sophisticated investment strategies. We focus on the standard variance which is a standard risk measure, the GARCH variance, the LPM(n) (the lower partial moment with degree n) and the CVaR (Note 2).

For the mean-risk optimization problem, we choose to minimize the risk while imposing a satisfactory level of return. Following (Nawrocki, 1992), we maintain constant the minimum return across the 18 rolling windows.

Mean-standard Variance strategy: In this framework, investors allocate assets by minimizing portfolio standard variance subject to budget constraint, non negativity of the weights and a minimum portfolio return constraint. (see Appendix I for more details).

Mean-GARCH variance strategy: This strategy is based upon an extension of the standard model of Markowitz allowing the leptokurtic phenomena observed in return series. Conditional heteroscedastic variances instead of traditional ones are used to compute optimal portfolios. The process GARCH (1, 1) is used to estimate the GARCH variances. This choice is inspired by Box and Jenkins (1976) who suggested that the more the estimated parameters are fewer, the more the estimation risk is lower. Portfolio optimization problems require the computation of the covariance matrix which includes the GARCH standard deviations already estimated, and the constant correlation matrix computed from historical data.

Mean-LPM(n) strategy: In this strategy, the variance is substituted by the lower partial moments which are a generalization of the semi variance, (see Appendix II for more details). Mean–LPM(n) is more coherent with investors rationality than the mean–variance and the mean-GARCH variance (Note 3). The LPM(n) risk measures focus on portfolio returns that are lower than a threshold rate.

Mean-CVaR strategy: This strategy is based upon mean-CVaR portfolio optimization problem in lines of the proposed approach of Rockafellar and Uryasev(2000, 2002). The CVaR is computed from historical data. The investor minimizes the CVaR subject to the same constraints advanced above. This strategy requires the choice of an appropriate confidence level β. However, there is not a consensus about the optimal confidence level. Also, Mato (2005) suggests that the confidence level does not affect results since CVaR is relatively stable to these changes. We choose two confidence levels (95% and 97%) that are not too high to avoid the dependence of results from the sample, nor too low to allow deviation from the traditional mean-variance strategy (Note 4).

3.1.2 Rolling Windows

The time frame is divided into 18 rolling windows. Every window contains an estimation period and a testing period; each one includes respectively 48 and 12 monthly observations. The last four years are retained as the most recent period (Note 5); this choice is motivated by Nawrocki (1991) who argues that a 48-estimation period is long enough to avoid errors in estimating optimization's input. Moreover, the choice of 48 observations is consistent with Moreno et al. (2005) where 50 weekly observations were used in the estimation period. The first window is as follows: the estimation period is based on observations 1–48, whereas, the test period is based on observations 49–60. The second estimation period starts at the 13th observation, and spreads to the 60st observation. The second test period starts from the 61th observation up to the 72nd, etc. Each estimation period allows the estimation of eight models in an ex ante context. The period immediately following enables the assessment of each model's estimated performance. Each portfolio is composed of the same set of investment opportunities with different weights. Unrestricted and restricted portfolios are considered in this study. Unrestricted portfolios constrain each asset weight between 0 and 1; while the latter takes into account the home bias phenomena and the capital markets investability.

3.1.3 Portfolios Evaluation

For comparison purposes, we apply a broad range of metrics to investigate, in an ex ante context, the out-of-sample economic and statistical performance of each portfolio investment strategy. To gauge the economic performance, we use the terminal wealth where the portfolios are revised at the end of each annual testing period using a 1% transaction fee. Note that the terminal wealth value represents the compound value of a \$1 investment in each rebalanced investment strategy portfolios along the 18 testing periods. For either domestic or equally weighted portfolios, it represents the compound value of a \$1 Investment in each one along the 18 testing periods. Besides, we employ a volatility measure to check if international portfolio diversification can reduce portfolio return variability compared to domestic investment strategies. Thus, we will focus on portfolio standard deviation which is a common measure of portfolio return variability across time. Our approach is in line with that of Abidin et al. (2004**)** (Note 6). We compute also the VaR (95%) as it may provide more accurate rankings of investment strategies under non-normality (Eling & Schuhmacher, 2007). We apply also two risk-adjusted performance measures. Indeed, the Sharpe ratio (**SR**) (Note 7) is used, as it is the common performance measure widely cited in the literature; (see, for example, Driessen & Laeven, 2007; Cain & Zurbruegg, 2010). However, the Sharpe ratio is subject to criticisms that are due basically to the normality hypothesis. Klemkosky (1973), and Ang and Chua (1979) have shown that the performance measures based upon normality, such as the Sharpe ratio, can lead to a wrong ordering. Moreover, DeFusco et al. (2011) cautions about interpreting negative Sharpe ratios; they argue: "Therefore, in a comparison of portfolios with negative Sharpe ratio, we cannot generally interpret the larger Sharpe ration (the one closer to zero) to mean better risk-adjusted performance", (DeFusco et al., 2011, pp.116). The semi variability (**SVR**) is used to overcome these limits; it is a variation of the Sortino ratio proposed by Sortino et al. (1991, 1996) which focuses on the "bad" volatility ratio, also called semi-volatility (Note 8**)**. The semi variability ratio is interesting for the investor averse to risk and basically concerned with downside risk.

$$SR_i = \frac{RP_i - rf_i}{\sigma_i} \tag{2}$$

$$SVR_i = \frac{RP_i - rf_i}{SD_i} \quad \text{(Note 9)} \tag{3}$$

3.2 Database

As mentioned before, the database consists of 41 monthly international index expressed in US dollar, covering the period from 29 January 1988 to 31 December 2009. We choose monthly frequency as (Nawrocki, 1991, 1992; Driessen & Laeven, 2007; Moreno et al., 2005; Gupta & Donleavey, 2009; Rockafellar & Uryasev, 2000; Statman & Scheid, 2008, Goetzmann et al., 2005). This choice enables us to deal with nonsynchronous return observation due to time zone difference between national stocks markets. The choice of country index is motivated by their behavior which is presumably more diverse than those of individual assets.

Several databases were used. The series are issued from the MSCI, the S&P/IFC and global index series (264 monthly observations). Twenty three developed markets and 18 emerging and frontier ones are considered. The developed markets are: Denmark, France, Germany, Italy, Japan, Netherlands, Norway, Switzerland, UK, Belgium, Canada, Sweden, Austria, Australia, Hong Kong, Ireland, Singapore, USA, Spain, Finland, Portugal, New Island and Greece. The emerging and frontier markets group includes: Argentina, Brazil, Chile, Mexico, India, Korea, South Africa, Thailand, Jordan, Malaysia, Pakistan, Philippine, Nigeria, Venezuela, Colombia, Turkey, Taiwan and Indonesia. Returns are calculated as the first difference of log prices. Domestic stock market index and the US dollar 1-Month euro dollar deposit rate are collected over the period running from January 1976 to December 2009. To ensure ex antes strategies, we form portfolios based on information available at the time of their composition ; thus, the minimum return is set equal to the average monthly return of domestic index over the ex ante period from 30 January 1976 to 31 December 1987. Calculated value is equal to 1% per month; this choice is consistent with the 1.1% used by Rockafellar and Uryasev (2000). Following Cain and Zurbruegg (2010) (Note 11), different rates values have been tested; tests with rates equal to 1.1%, 0.9% and 1% have shown similar results. Thus, we retain the 1% minimum monthly of return.

Similarly, we set the threshold level for LPM(n) measures equals to the mean return of the US dollar 1-Month euro dollar deposit rate for the ex ante period running from 30 January 1976 to 31 December 1987 so that we ensure ex ante investment strategies. The calculated rate is equal to 0.8% per month and it corresponds exactly to the rate used by Nawrocki (1992). Hence, relative to this risk measure, monthly returns less than 0.8% are considered risky. As expected, all return series show excess kurtosis, (the kurtosis is above 3). With few exceptions (Argentina, Colombia, Venezuela, Indonesia, Korea, Jordan, Greece, Japan), almost all the series are negatively skewed. As shown in table 1, the P-value of Jarque Bera statistics (J-B) shows that all the series, except for Japan are not normally distributed. Also, the Ljung-Box test was applied to the squared returns of order 12. Results show that with few exceptions, autocorrelation is detected, in the squared returns, suggesting that a GARCH parameterization for the second moments may be appropriate.

Table1. Descriptive statistics of the continuous monthly return series

	Mean	**Max**	**Min**	**Std, Dev,**	**Skewness**	**Kurtosis**	**Prob.J-B**	**Q square(12)**
Argentina	0,013	0,670	-0,539	0,148	0,354	6,958	0,0000	54,846
Brazil	0,017	0,591	-1,095	0,159	-1,413	12,649	0,0000	26,960
Chile	0,015	0,200	-0,344	0,072	-0,661	5,898	0,0000	16,656
Colombia	0,015	0,317	-0,292	0,089	0,164	4,525	0,0000	84,080
Mexico	0,017	0,254	-0,419	0,096	-1,022	6,195	0,0000	16,596
Venezuela	0,019	0,532	-0,492	0,121	0,157	6,856	0,0000	35,486
India	0,011	0,538	-0,921	0,117	-1,795	18,967	0,0000	2,064
Indonesia	0,009	0,665	-0,520	0,142	0,162	7,325	0,0000	47,733
Korea	0,006	0,534	-0,375	0,110	0,190	5,629	0,0000	116,010
Malaysia	0,007	0,406	-0,360	0,086	-0,259	6,983	0,0000	227,860
Pakistan	0,008	0,316	-0,527	0,105	-0,646	7,159	0,0000	24,002
Philippine	0,005	0,360	-0,346	0,093	-0,164	4,820	0,0000	36,529
Taiwan	0,005	0,381	-0,410	0,108	-0,080	4,259	0,0001	60,321
Thailand	0,006	0,359	-0,416	0,115	-0,537	5,136	0,0000	122,620
Turkey	0,010	0,550	-0,532	0,167	-0,065	3,871	0,0140	9,327
Jordan	0,008	0,276	-0,224	0,059	0,356	5,876	0,0000	65,264
Nigeria	0,012	0,691	-1,211	0,129	-3,027	37,162	0,0000	0,829
South Africa	0,014	0,171	-0,391	0,062	-1,255	9,197	0,0000	5,405
Australia	0,009	0,164	-0,295	0,059	-0,710	5,504	0,0000	42,116

Austria	0,006	0,227	-0,463	0,078	-1,315	9,819	0,0000	96,479
Denmark	0,010	0,168	-0,297	0,058	-0,921	6,261	0,0000	47,470
France	0,008	0,191	-0,254	0,059	-0,623	4,694	0,0000	48,447
Germany	0,007	0,213	-0,279	0,067	-0,843	5,480	0,0000	42,297
Greece	0,008	0,440	-0,457	0,101	0,285	6,710	0,0000	39,597
Hong Kong	0,010	0,287	-0,341	0,077	-0,281	5,219	0,0000	29,438
Ireland	0,007	0,208	-0,228	0,061	-0,607	4,714	0,0000	60,131
Italy	0,005	0,196	-0,269	0,068	-0,297	3,962	0,0009	40,581
Japan	0,000	0,217	-0,215	0,064	0,031	3,619	0,1190	45,508
Netherlands	0,009	0,134	-0,289	0,056	-1,368	7,303	0,0000	52,054
New Zealand	0,004	0,244	-0,254	0,068	-0,342	4,285	0,0000	19,446
Norway	0,009	0,194	-0,406	0,078	-1,345	7,854	0,0000	60,502
Portugal	0,004	0,250	-0,304	0,066	-0,364	5,135	0,0000	6,335
Singapore	0,008	0,230	-0,342	0,074	-0,717	6,168	0,0000	54,580
Switzerland	0,009	0,154	-0,170	0,050	-0,412	4,002	0,0001	34,471
UK	0,007	0,141	-0,210	0,048	-0,367	4,580	0,0000	61,179
USA	0,008	0,108	-0,188	0,043	-0,835	4,810	0,0000	50,117
Belgium	0,007	0,225	-0,455	0,064	-2,073	15,309	0,0000	42,500
Canada	0,008	0,193	-0,314	0,057	-1,121	7,652	0,0000	29,272
Finland	0,008	0,287	-0,382	0,094	-0,359	4,472	0,0000	49,012
Spain	0,009	0,197	-0,291	0,066	-0,684	5,208	0,0000	21,948
Sweeden	0,010	0,227	-0,310	0,076	-0,640	4,826	0,0000	31,581

Notes: The table shows the descriptive statistics for each of the countries index. The mean, maximum (max), minimum (min), standard deviation (Std. dev.), skewness and kurtosis. The p-value of the Jarque–Bera statistic, for testing the null hypothesis that the return series are normally distributed, is also shown. Q square (12) is the Ljung-Box statistic of order 12 applied to the squared returns. All the data is shown on decimal terms.

4. Results and Discussion

Table 2 shows average terminal wealth values for portfolio investment strategies from 1992 to 2009 in an unrestricted context. A terminal wealth of 7.30 is interpreted as an initial investment of $1 in 1992 growing to $7.30 by the end of 2009. We notice that domestic portfolio provides the least terminal wealth value ($3.13). Thus, the American investor who invests in 1992 in local market earns the lowest compound return by 2009. Indeed, according to the terminal wealth criteria, all the international portfolio diversification strategies are beneficial for an American investor.

Moreover, American investors who follow a naive strategy will earn a 34.4% higher return than when investing in the home market. However, this terminal wealth is still lower than those achieved by optimal international investment strategies. A standard mean-variance investment strategy obtains the third worst terminal wealth value but it is still 89.2% higher than those of the domestic portfolio.

Therefore, to further assess the robustness of international portfolio diversification, the four statistical performance measures are calculated across the 18 testing periods for each portfolio investment strategy. To gain space, only arithmetic average values are reported in table 2. More detailed results are provided upon author request. Friedman test is also undertaken to check the robustness of the four statistical performance measures.

First, we observe the risk-based performance measures; as we can see, in terms of SR, on average, the domestic investment strategy achieves the lowest performance and the naive investment strategy follows. This finding supports the benefit of portfolio diversification. Also, this result is consistent with Michaud et al., (1996) who highlighted the increase of return per unit of risk relative to a U.S.-only portfolio. Moreover, results relative to the domestic and to the naive investment strategies support those of terminal wealth and annualized portfolio returns criteria.

Conversely, results according to the SVR do not support the relevance of international portfolio diversification since the domestic investment strategy lead to the highest value (2.55). However, this result seems less robust since it produces the highest standard deviation across the 18 testing periods (6.58) compared to other investment strategies. Not statistically significant difference exists among the investment strategies according to the shape ratio and the semi variability ratio as the p-values equals to 0.775 and 0.948 respectively. We think that this finding may be partly due to the dependence of the out-of sample's performance on the accuracy of the prediction of the expected returns (Note 12).

Table 2. Performance of unrestricted portfolio investment strategies: an out-of-sample analysis for unrestricted portfolios

		CVAR95	**CVAR 97**	**Variance**	**GARCH**	**LPM2**	**LPM3**	**LPM4**	**LPM5**	**Naive**	**Domestic**	**p-value**
SR	***Mean***	0,919	0,943	0,973	1,052	1,066	1,096	1,047	0,986	0,831	**0,797**	0.775
	Std.Dev	2,32	2,37	1,83	1,99	1,91	1,98	2,00	2,01	1,84	1,76	
	ranking	**8**	**7**	**6**	**3**	**2**	**1**	**4**	**5**	**9**	**10**	
SVR	***Mean***	2,008	2,055	1,748	1,989	1,954	2,061	2,173	2,324	1,885	2,549	0.948
	Std.Dev(%)	3,73	3,72	2,77	3,18	3,03	3,03	3,43	4,10	3,34	6,58	
	ranking	**6**	**5**	**10**	**7**	**8**	**4**	**3**	**2**	**9**	**1**	
VaR (95%)	***Mean***	0,075	0,075	0,056	0,073	0,055	0,056	0,061	0,066	0,073	0,060	0,019
	Std.Dev	0,07	0,07	0,05	0,06	0,05	0,04	0,04	0,05	0,07	0,05	
	ranking	**9**	**9**	**2**	**7**	**1**	**2**	**5**	**6**	**7**	**4**	
Annualized Std.Dev.	***Mean(%)***	13,237	13,527	12,097	15,744	12,204	12,686	13,714	14,846	15,529	13,097	
	Std.Dev	5,09	5,40	4,25	5,32	4,40	4,99	6,12	7,28	7,14	6,31	0.001
	ranking	**5**	**6**	**1**	**10**	**2**	**3**	**7**	**8**	**9**	**4**	
Terminal Wealth	***Value***	7,30	7,92	5,92	7,05	7,38	8,03	7,94	7,20	4,21	3,13	
	Ranking	**5**	**3**	**8**	**7**	**4**	**1**	**2**	**6**	**9**	**10**	

Notes: This table shows the final wealth value of an initial investment of $1 from 1992 to 2009. The table also shows the mean and standard deviation of each SR, SVR, annualized standard deviation (Annualized Std.Dev.) and annualized VaR (95%). It also shows the ranking of each portfolio investment strategy according to each criteria. The table shows also the results from Freidman's bilateral test of variance by rank; the null hypothesis is that each of the 4 statistical criteria are identically distributed. We apply the square root of time rule to compute annualized standard deviation and the annualized value at risk. A p-value greater than 0.05 indicates the acceptance of the null at the 5% statistical significance level. The portfolio of each optimization based investment strategy (mean-variance, mean-GARCH variance, mean-CVaR95, mean-CVaR97, mean-LPM2, mean-LPM3, mean-LPM4, mean-LPM5) is reallocated each year according to an optimization problem. Each optimal portfolio is built using 48 monthly observations before the starting date of each testing period. The portfolio of each optimization- based investment strategy is unrestricted, thus the weight for each index belongs to [0,1].

Surprisingly, according to the annualized standard deviation of portfolio returns (Note 13), the domestic portfolio is not, on average, the most volatile. Indeed, 6 international portfolios produce variability returns higher than those of domestic one. As expected, the mean-variance investment strategy is the most interesting to reduce the portfolio returns variability, since it focuses on the reduction of the overall dispersion. Results according to VaR(95%) supports those of annualized standard deviation; indeed according to the value at risk criteria, domestic portfolio produces the fourth lowest loss compared to other investment strategies. Note, however, that the results according to annualized standard deviation and to the VaR(95%) are robust along all the testing periods. Results are also statistically significant between investment strategies according to the annualized VaR(95%) and the annualized standard deviation (p-value equals respectively to 0.019 and 0.001) which support our finding.

Thus, this finding sustains the fact that there is not a conclusive result showing that internationally unrestricted diversified portfolios reduce the returns variability as well as the minimum loss in the 5% worst cases. If this is the case, this result is not good news for the manager, as Solnik (1974) states:" the primary motivation in holding a portfolio of stocks is to reduce risk”.

Thereafter, we check optimal portfolio composition in terms of the domestic market and also in terms of Emerging and Frontier versus developed markets. Table 3 reports the average allocation of the domestic market (USA) for each international optimal investment strategy. As we can see, on average, domestic market weight is relatively low: it ranges from 2.63% to 33.85% for the different international optimal portfolios. Thus, the international component is more dominant in optimal portfolios. At first glance, the international component in optimal portfolio has magnified portfolio volatility.

Table 3. Average weights for USA market and each international investment strategy for the 18 testing periods

	VARIANCE	GARCH	LPM2	LPM3	LPM4	LPM5	CVAR95	CVAR97
USA	17,57	2,63	23,63	29,28	32,58	33,85	5,14	4,91

Note: The table shows average weights of market indexes for 8 investment strategies generated from optimization problems during the 18 testing period. The currency used is the US dollar. All the values are given in %.

Results of optimal allocation in each group of markets are reported in table 4. As we can see, for most investment strategies, when we consider the whole 18 testing periods, the average allocation in Emerg. markets in optimal portfolios is greater than those in developed ones. Moreover, the asset allocation in Emerg. markets are substantially high for the remaining investment strategies as the lowest proportion is equal to 42.41%.

Table 4. Unrestricted’ portfolio average composition in emerging and developed markets across the 18 testing periods

		Mean	Std.dev.	p-value
CVAR95	**Emerg.**	70,81	20,02	0,018
	Dev.	29,19		
CVAR 97	**Emerg.**	72,54	19,86	0,018
	Dev.	27,46		
Variance	**Emerg.**	56,76	22,08	0,346
	Dev.	43,24		
GARCH	**Emerg.**	76,20	8,89	0,000
	Dev.	23,80		
LPM2	**Emerg.**	53,16	26,98	0,637
	Dev.	46,84		
LPM3	**Emerg.**	48,92	32,18	0,346
	Dev.	51,08		
LPM4	**Emerg.**	45,61	35,19	0,157
	Dev.	54,39		
LPM5	**Emerg.**	42,41	37,12	0,059
	Dev.	57,59		

Note: This table shows the average composition of unrestricted optimal portfolio for each optimization model in terms of percentage invested in emerging, frontier and developed markets across the 18 test periods. To simplify the notation, Emerg. includes both emerging and frontier markets. The table shows also the calculated standard deviation of allocations in each Emerg. and developing markets group allocations across the 18 testing periods. The table reports the p-values for Wilcoxon’s rank sum test where the null hypothesis is that equity allocations for each investment strategy in each group of countries are identically distributed along the 18 testing periods. The optimization models are (mean-CVaR95, mean-CVaR97, mean-variance, mean-GARCH variance, mean-LPM2, mean-LPM3, mean-LPM4 and mean-LPM5). The weight for each index belongs to [0,1].

When we consider Emerg. market allocations from period to period, results are, in general persistent for the mean-variance, mean-GARCH, mean-CVaR (95, 97) investment strategies. Indeed, the calculated standard deviations across the 18 testing periods show that these strategies are the most robust. The Wilcoxon test is also performed to test for equal distribution for Emerg. versus developed markets allocation. Results show that only mean-CVAR (95, 97) and mean-GARCH investment strategies lead to statistically different asset allocation between Emerg. and developed markets across the 18 testing periods. On the contrary, other investment strategies that did not highlight a statistically significant difference in asset allocation between either Emerg. or developed groups of markets are the least robust since they perform higher standard deviation across the 18 testing periods.

As this finding highlights the relevance of emerging and frontier markets in international equity investment strategies for an American investor, we acknowledge that our prior result might be explained by the high presence of emerging markets in unrestricted optimal portfolios. Indeed, we would think that the impact of introducing emerging and frontier markets in internationally diversified portfolios is not interesting in terms of global volatility as well as minimum loss reduction. This finding might be explained by the higher volatility measured by the standard deviation of continuous monthly returns of emerging markets compared to developed ones as reported in Table 1.

Table 5. A summary of stylized facts for a selection of capital markets included in the study

Markets	Stocks traded turnover ratio (%)	Market Capitalization (usd) 2009	Market capitalization (% of GDP) 2009
Venezuela	0,8	8,860,000,000	2,7
Argentina	5,4	48,932,431,697	15,9
Nigeria	11	33,324,902,304	56,5
Columbia	11,8	133,301,343,553	56,5
Chile	22	209,475,269,305	130,2
Philippine	26	80,132,276,289	47,6
Mexico	26,9	340,564,590,896	38,6
Malaysia	32,9	255,952,052,510	132,7
New Island	39,5	67,061,169,518	52,9
Jordan	40,3	31,864,812,614	127

Notes: Market capitalization in US dollars, market capitalization as % of GDP and turnover ratio. Data was collected from (http://data.worldbank.org/). Because the turnover ratio for Venezuela in 2009 was unavailable in the world bank website, we suppose that it was the same as in 2008.

Therefore, we perform a more in-depth study of the benefits of international portfolio diversification relative to different performance measures; we combine an internationally diversified portfolio to a pure U.S. one with a 50/50% proportion. Hence, we can observe how the increase of a pure U.S. component into an internationally diversified portfolio would have impacted the performance measures. This procedure should lead to more realistic portfolios while taking into account the home bias phenomena, which is well documented in the literature, (see, for example, French & Poterba, 1991; Lewis, 1999; Chan et al., 2005; Secru & Vanpee, 2007). Also, it is consistent with the investor's attitude who may be hesitant to assign a major portion of his portfolio to foreign markets, especially in emerging markets which exposes them to risk.

As Barry et al. (1998) reported that investors prefer to trade in liquid markets, we follow Barry et al. (1998), Kortas et al. (2006) among others and we use the market turnover ratio (Note 14) as an indicator of market liquidity. Data was collected from the World Bank website (http://data.worldbank.org/). We have excluded less liquid markets from the study because they are perceived to have higher transaction market costs and access may be difficult for foreign investors, thus eroding the potential benefits of diversifying into these markets.

Table 5 shows the main features of an investment subset especially the turnover ratio. Indeed, to gain space, we report the tenth market associated to the lowest turnover ratio. The first column shows the turnover ratios of the retained markets; the second column shows the capitalization in USD of each market; this latter indicates financial market size. The last column shows market capitalization as a percentage of the GDP of the economy. Venezuela has the lowest turnover ratio followed by Argentina, Nigeria, Columbia and Chile. We exclude the fourth lowest markets in terms of turnover ratio; thus, we retain Chile in our investment set since the turnover ratio and the market capitalization are almost two times those of Columbia. Therefore, restricted portfolios were composed in two steps: First, optimal international portfolio was computed from the new investment set excluding Nigeria, Argentina, Columbia, Venezuela and USA. Second, the international portfolio already built and the domestic index were combined in a proportion 50% versus 50%.

As we can see in Table 6, results for all restricted portfolio optimization strategies lead, on average, to higher terminal wealth and Sharpe ratio values than those of the domestic one. The calculated standard deviation for Sharpe ratio shows that SR results are also robust across time. According to the average SVR, the ranking of domestic portfolio drop to the sixth as it was ranked first in an unrestricted context. Indeed, the irrelevance of the domestic portfolio regarding the SVR becomes more pronounced in a portfolio restricted context. This finding supports the benefit of international diversification in a restricted context, although results according to the SVR seem not robust across time. We note that the naïve investment strategy slightly dominates the domestic portfolio according to the Sharpe ratio. Interestingly, the domestic portfolio obtains clearly a higher ranking (seventh) relative to the average annualized standard deviation of portfolio returns as well as to the value at risk (95%) criteria. Thus, when we increase the domestic component in the optimal internationally diversified portfolio, international investment strategies become more advantageous in volatility and minimum loss reduction. Results are also consistent through time. The naïve investment strategies seem less performant according to both criteria. The Freidman statistic test highlights a statistically significant difference only for the annualized standard deviation (p-value equals to 0.000).

We conclude that, when we decrease the international component, especially the emerging and the frontier markets component, the relevance of international equity diversification becomes obvious.

Thereafter, we performed a comparison between unrestricted portfolios and restricted ones according to the performance measures employed. We also performed a Wilcoxon test to test the null hypothesis that statistical performance measures in a restricted and unrestricted context are identically distributed along the international investment strategies; results are reported in Table 7.

Not surprisingly, the restricted international strategies lead to lower terminal values than unrestricted ones. Thus, when the weight of the pure U.S. portfolio is constrained to be 50% of the overall portfolio, the investor seems to be achieving lower economic gains compared to an unrestricted portfolio. This finding provides a further insight for the economic benefit of adding international investment to an American investor. Also, it supports the idea that emerging markets enhance the economic gains of international equity diversification. Conversely, we highlighted a decrease in all annualized standard deviations when we moved from an unrestricted to a restricted context. Moreover, with few exceptions, this finding is true for value at risk criteria. Note also that the Wilcoxon test highlights a statistically significant difference between unrestricted and restricted optimal portfolio among international investment according to the annualized standard deviation (p-value equals to 0.012); however we fail to highlight a presence of a statistically significant difference between unrestricted and restricted optimal portfolios among international investment according to the VaR(95%) (p-value equals to 0.069). Intuitively, we would suggest that when we decrease the international component, and especially the emerging and frontier markets component allocation in the diversified portfolio, we reduce, in most cases, the variability and the minimum loss in the 5% worst cases. Because emerging markets are substantially present in optimal unrestricted portfolios, our finding supports the widely held belief that emerging markets enhance the economic performance of internationally diversified portfolios. However, contrary to the results often presented in the literature, we found that the lower the proportion of emerging markets in optimal portfolios, the lower the annualized standard deviation and the minimum loss in portfolio returns.

Results according to risk adjusted-based performance measures are quite ambiguous. On one hand, relative to the SR, restricted optimal portfolio occasionally dominates the unrestricted one. The calculated standard deviation shows that this result is also robust across time. And in the other hand, the SVR provides the most significant result which highlights an increase along all international investment strategies when we move from unrestricted to restricted context. However, Freidman test highlights a statistically significant difference between unrestricted and restricted optimal portfolio among international investment according to both the SR (p-value equals to 0.036) and the semi variability ratio (p-value equals to 0.012), however, as we highlighted earlier, we believe that the SVR is the most powerful risk adjusted performance measure.

In sum, our study highlights the benefit of international equity investing. The emerging and frontier markets are an important component of well-diversified equity portfolios. However, we should be cautious about the component invested in this class of assets. Our findings may be consistent with those of Masters (1999) and Bekaert and Urias (1999) who suggested that return enhancement and volatility reduction occur when between 5% and 10% of the equity portfolio is committed to emerging markets. This result is likely to be unexpected because emerging markets are supposed to decrease returns variability once introduced in international portfolios because of their low correlation between developed markets. However, a plausible explanation is that due to the high increase of correlation between emerging and developed markets, especially the U.S. market, the correlation of emerging markets with the U.S. stock market may have increased over time, (Garza-Gómez & Metghalchi, 2006). Thus, the correlation becomes inefficient to offset the high volatility of emerging and the frontier markets.

Table 6. Performance of unrestricted portfolio investment strategies: an out-of-sample analysis for restricted portfolios

		CVAR95	CVAR 97	Variance	GARCH	LPM2	LPM3	LPM4	LPM5	Naive	Domestic	p-value
RS	***Mean***											
	Std.Dev.	1,84	1,85	1,74	1,82	1,72	1,67	1,66	1,68	1,84	1,76	
	ranking	**3**	**1**	**5**	**2**	**4**	**6**	**8**	**6**	**9**	**10**	
SVR	***Mean***	**3,395**	**3,477**	**2,805**	**6,587**	**2,776**	**2,492**	**2,476**	**2,554**	**1,885**	**2,549**	0,929
	Std.Dev.	6,67	6,66	4,37	19,09	4,46	3,72	3,70	3,92	3,34	6,58	
	ranking	**3**	**2**	**4**	**1**	**5**	**8**	**9**	**6**	**10**	**6**	
Annualized	***Mean(%)***	12,460	12,379	11,480	13,188	12,187	12,530	12,963	13,448	15,529	13,097	0,000
Std.Dev.	***Std.Dev.***	4,70	4,81	5,28	6,20	5,24	4,99	5,08	5,48	7,14	6,31	
	ranking	**4**	**3**	**1**	**8**	**2**	**5**	**6**	**9**	**10**	**7**	
VaR (95%)	***Mean(%)***	5,737	5,698	5,281	6,159	5,742	5,817	5,963	6,171	7,316	6,003	0,126
	Std.Dev.	0,04	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,07	0,05	
	ranking	**5**	**2**	**1**	**8**	**3**	**4**	**6**	**9**	**10**	**7**	
Terminal	***value***	5,28	5,76	3,76	4,46	4,20	4,50	4,58	4,42	4,21	3,13	
Wealth	***ranking***	**2**	**1**	**9**	**5**	**8**	**4**	**3**	**6**	**7**	**10**	

Notes: This table shows the final wealth value of an initial investment of $1 from 1992 to 2009. This table also shows the mean and standard deviation of each SR, SVR, annualized standard deviation (Annualized Std.Dev.) and annualized VaR(95%). It also shows the ranking of each portfolio investment strategy according to each criteria. We apply the square root of time rule to compute annualized standard deviation and the annualized value at risk. The table also also the results from Freidman's bilateral test of variance by rank; the null hypothesis is that each of the 4 statistical criteria are identically distributed. A p-value greater than 0.05 indicates the acceptance of the null at the 5% statistical significance level. The portfolio of each optimization based investment strategy (mean-variance, mean-GARCH variance, mean-CVaR95, mean-CVaR97, mean-LPM2, mean-LPM3, mean-LPM4, mean-LPM5) is reallocated each year according to an optimization problem. Each optimal portfolio is built using 48 monthly observations before the starting date of each testing period. The portfolios issued from the first 8 strategies are restricted. The restricted portfolio is a combination between an international portfolio excluding the USA, and a domestic index comprised of 50% each.

Table 7. Statistical comparison between restricted and unrestricted statistical performance measures

Performance Criteria	Annualized Std.Dev.	SR	SVR	VaR(95%)
p-value	0.012	0.036	0.012	0,069

Note: The table reports the p-values for Wilcoxon's rank sum test where the null hypothesis is that statistical performance measures in a restricted and unrestricted context are identically distributed along the international investment strategies. A p-value greater than 0.05 indicates the acceptance of the null at the 5% statistical significance level.

5. Conclusions

This study examines the benefits of international portfolio diversification across different investment strategies based on different risk measures from the perspective of an American investor. Equity returns from 41 countries are used, including both developed, emerging and frontier markets, over the period 1988–2009 which has been characterized by increasing market correlations and crises occurrence. Different portfolios were constructed and re-balanced in 18 testing periods. An equally weighted portfolio and a domestic one were also used as benchmarks.

The main conclusion is that, when a 1% transaction fee is applied at the end of each annual testing period, economic gains from international equity diversification are still substantial to an American investor. Results remain robust when we consider restricted optimal portfolios, while leading to lower terminal wealth values.

We highlight that emerging and frontier markets present the dominants or at least a substantial component in unrestricted equity portfolio. Hence, it is clear that international equity investment leads to significant economic gains; the latter is lower when we increase the domestic component and thus reduce the emerging and frontier markets components in an internationally diversified portfolio.

We found that unrestricted international diversification does not allow a reduction of the volatility and the minimum loss of portfolio returns compared to a pure-US portfolio. Conversely, international equity diversification allows portfolio returns volatility and minimum loss reduction only when we assign 50% of the overall investment to a domestic portfolio and the remaining 50% to a well diversified equity portfolio.

Given the high proportion of emerging markets in optimal unrestricted portfolios, we conclude that the lower is the proportion of emerging markets in optimal portfolios, the lower the annualized standard deviation and minimum loss of portfolio returns.

Interestingly, while for all optimization based strategies economic gains drop when we move from unrestricted to restricted investment, the risk-based adjusted performance measure record a substantial enhancement. Also, results are robust and statistically significant.

We conclude that the relevance of emerging and frontier markets is obvious when their presence is not substantial in an internationally diversified equity portfolio. Thus portfolio managers should be cautious about the component invested in this class of assets. We think that this finding is probably due to an increase of the correlation of emerging and frontier markets with developed ones, especially the U.S. market.

We conclude that unrestricted portfolios are more attractive to investors who look for economic gains; however, restricted portfolios are more interesting for an investor who seeks volatility and minimum loss reduction. Indeed, a restricted portfolio allows a substantial increase of performance adjusted to risk measured by the semi variability ratio. We contribute to the existing literature by highlighting the necessity to moderate the emerging and frontier markets in a well diversified equity portfolio.

An interesting extension of this study may be to check the maximum value of the component of emerging and frontier markets that could be committed to an internationally diversified equity portfolio. The objective of which would be to enhance the risk–based performance.

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Notes

Note 1. We acknowledge that the market reclassification problem also concerns the promotion of emerging markets to developed ones and the downgrade of developed markets to emerging ones.

Note 2. The VaR is excluded because it doesn't respect the sub additively condition, (see, Artzner et al., 1999; Acerbi & Tasche, 2002; Szergõ, 2002). Also, contrary to the VaR, the CVaR has an equivalent Linear programming formulation and can be solved using standard linear programming methods.

Note 3. The reason for this is that the LPM (n) is calculated from the downside distribution of returns, whereas the standard variance and the GARCH variance are calculated from the whole return distribution.

Note 4. Uryasev et al. (2002) suggest that larger deviations between mean-CVaR and mean variance efficient frontiers occur at higher confidence levels.

Note 5. Only past returns were used as explanatory variables for the returns of each series. Following Franses and Dijk (2000), we suppose, with some degree of market efficiency, that most of the information is included in recent returns.

Note 6. Note, however, that the authors point out that the risk of foreign equity investment is represented by the standard deviation of returns and the currency exchange rate risk. In this paper, we don't take into account the second risk.

Note 7. The Sharpe ratio is a special case of Roy's "safety first" ratio introduced by Roy (1952) where the disaster level (d) is replaced by the risk free level.

Note 8. Grootveld and Hallerbach (1999) used the Mean-downside risk Sharpe ratio name.

Note 9. Calculated Semi variability ratio is based on the annualized semi deviation, annualized portfolio return for each test period i (RPi) and the annualized risk free for each test period i (rfi). Semi deviation that is the root of semi variance; SDi is the annualized semi deviation of portfolio return (RPi) at testing period i.

Note 10. r is the threshold level of return, and F is the cumulative distribution of the return series.

Note 11. Cain and Zurbruegg (2010) constrained risk and not returns.

Note 12. Indeed, the adjusted-risk performance measures are return dependent. As Merton (1980) reported: "the estimates of variances or co variances from the available time series will be much more accurate than the corresponding expected return estimates".

Note 13. It has documented that, in presence of volatility clustering, the square root of time rule scaling is inappropriate and leads to an overestimation of the variability of long-horizon volatility; (Diebold et al., 1997). On the contrary, Wang et al. (2011) show that the SRTR may leads to a systematic underestimation (overestimation) of risk when the return follows a persistent (mean-reverting) process. However, Wang et al. (2011) argued that the underestimation resulting from the dynamic dependence structure is counterbalanced by the overestimation resulting from the excess kurtosis and jumps; hence, they show that SRTR scaling can be appropriate in some cases. Thus, we use the square root of time rule (SRTR) to scale risk.

Note 14. It is calculated by dividing the average market capitalization of the year by the total value traded.

Appendices

Appendix 1. This strategy is based upon the traditional approach of portfolio choice of Markowitz. The optimization problem is as follows:

Minimize X' Q X SC/

$$\sum_{i=1}^{n} x_i = 1 \text{; i: 1…41;} \tag{1.1}$$

$$\text{Lb =< xi <= ub; i: 1…41;} \tag{1.2}$$

$$\sum_{i=1}^{n} x_i * R_i \text{ >= minimum portfolio return} \tag{1.3}$$

Where Q is the covariance matrix with dimension (41, 41). The correlation matrix is embedded in the covariance matrix. The correlation matrix is calculated from historical data for each estimation period. It is supposed constant for each estimation period, however, it changes from one estimation period to another.

Appendix 2. The formula of the lower partial moment for level n and for asset i is as follows:

$$LPM(n,i) = \frac{1}{T}\sum_{t=1}^{T}\left[Maximum\{0,(\phi - R_{it})\}\right]^n \tag{2.1}$$

Where n is the level of lower partial moments, T is the number of observations, Φ is the threshold level, R_{it} is the return of asset i ; the more n is high, the more the investor is averse toward risk. For n=1 the investor is neutral toward risk, for n lower than one, the investor is a risk seeker. Following Moreno et al. (2005), this study computes LPM with n=2, 3, 4 and 5 to reflect different degrees of risk aversion and hence different attitudes toward risk. We consider four strategies for this family of risk measure: mean-LPM2, mean-LPM3, mean-LPM4 and mean-LPM5.

For a couple of assets i and j, the co-lower partial moments matrix can be defined according to Bawa (1975) and Fishburn (1977) as follows:

$$CLPM_{ij,n-1} = \frac{1}{T}\sum_{t=1}^{T}\left(\left[Max\{0,(\phi - R_{it})\}\right]^{n-1}(\phi - R_{jt})\right) \tag{2.2}$$

The CLPMij is not symmetric; however the Markowitz model requires a symmetric matrix. Nawrocki (1991) reformulates this co matrix to remedy this problem, thus he obtained a symmetric matrix that can be integrated in the model of Markowitz:

$$CLPM_{ij} = LPM_i LPM_j r_{ij} \tag{2.3}$$

Where r_{ij} is the correlation between two series i and j.

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