178b

IMPROVING PORTFOLIO PERFORMANCE ON EMERGING MARKETS USING DATA ENVELOPMENT ANALYSIS

José Luis Miralles-Quirós

University of Extremadura

Av. Elvas s/n 06006 Badajoz (Spain)

María Mar Miralles-Quirós

University of Extremadura

Av. Elvas s/n 06006 Badajoz (Spain)

José Manuel Nogueira

Polytechnic Institute of Tomar

Av. Dr. Aurélio Ribeiro 3, Tomar (Portugal)

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ÁREA TEMÁTICA: B) VALORACIÓN Y FINANZAS

Improving Portfolio Performance on Emerging Markets using Data Envelopment Analysis

Abstract

In recent years, researchers have analyzed emerging markets from several points of view due to their importance in global economy. This study examines different rules of portfolio construction using exchange-traded funds (ETFs) from eighteen emerging markets and employs Data Envelopment Analysis (DEA) to select the efficient ones. We show that a first step where the DEA approach is used for selecting the ETFs leads investors to outperform not only the naïve strategy but also the classical portfolio optimizations with any of the two strategies that are developed just using the emerging markets selected by the DEA.

1. Introduction

The transformation of emerging countries with major geopolitical, economic and demographic changes has been remarkable in recent years and has led investors to wonder if they should invest in these markets. The answer should be usually affirmative, however, the fact that their stock markets have shown no net earnings growth for the past 8 years (2011-2018), in spite of there being the conviction on investors that they could be changing for the better, means that the doubt of whether they are able to be considered a real investment alternative for investors or not still remains.

This study covers eighteen emerging markets and examines different portfolio construction rules in order to compare their performances. We improve the previous empirical literature by using Exchange Traded Funds (hereafter ETFs) which offer an alternative for investing in these markets by tracking of passive benchmark indices on them. These assets are very similar to open-ended funds, but they can be transacted at market price any time during the trading day and, accordingly to Basu and Huang-Jones (2015), they should be considered to be an option for investing instead of mutual funds in absence of superior risk-adjusted performance because they can provide similar diversification opportunities at a lower cost.

Additionally, we suggest using the potential of the Data Envelopment Analysis (DEA hereafter) procedure for selecting the efficient emerging markets and using them for estimating the asset allocation on different strategies. The DEA approach has been extensively used in performance appraisal in previous empirical literature from the initial studies of Farrel (1957) and Charnes et al. (1978) with particular reference to the field of mutual funds (See Solórzano-Taborga et al., 2018, who summarized the main works on DEA and mutual funds highlighting the inputs and the outputs used in each work) but to the best of our knowledge there are no studies which mix the use of the DEA procedure and asset allocation techniques to estimate the optimal portfolio weights in emerging markets.

We find that the previous step of choosing the efficient ETFs by using the DEA approach leads to clear performance improvements compared to the equally weighted portfolio but also outperforms classical portfolio optimization models. We obtain mainly positive portfolio performances in all cases when the portfolios are formed considering the DEA procedure but negative in most of the other cases. It is also interesting to point out that in all portfolio optimizations Asian markets exhibit the highest allocation weights in contrast to the rest of the emerging markets.

The rest of the paper is organized as follows. In Section 2, we present a literature review about emerging markets. Section 3 describes the theoretical background of this paper by explaining the methodology employed to construct and evaluate the strategies. In Section 4, the database is defined and the descriptive statistics are analyzed. Section 5 reports the empirical results of the proposed investment strategy. Section 6 provides the robustness test results. Finally, Section 7 provides the main conclusions.

2. Literature review

Researchers have analyzed emerging markets from several points of view due to their importance in global economy. Li et al. (2003) use monthly total returns of MSCI indices from developed and emerging countries (Latin American and Asian) focusing on the period from January 1976 to December 1999. They use the mean-variance framework (MV hereafter) and show that the international diversification benefits remain substantial for US investors if they are subject to short-sale constraints in emerging markets.

Pavabutr (2003) proposes the mean-lower partial moment (MLPM) as an alternative to the MV approach. Using monthly returns of different indices from emerging countries, he shows that the MLPM approach outperforms the MV criteria during bearish periods.

Gottesman and Morey (2007) examine the ability of emerging market mutual funds characteristics during the period 1997-2005 finding that the expense ratio is the only one that consistently predicts future fund performance.

Michelson et al. (2008) employ monthly returns of emerging market mutual funds over the 1999-2005 period in order to investigate their performance. They conclude that emerging market funds present a heterogeneous behavior outperforming and underperforming different indices.

Lai and Lau (2010) examine the portfolio performance of Malaysian mutual funds using the Fama and French three-factor model and the Carhart four-factor model using data from 1990 to 2005. They find evidence that these funds yield superior return than benchmark indices. More recently, Basu and Huang-Jones (2015) investigate the performance of globally diversified emerging market equity funds over the period from August 2000 to July 2010 finding that these funds do not outperform the market benchmark index.

In this investment context, the spectacular growth of the number of ETFs and their advantages when compared to mutual funds have turned them into an interesting alternative for getting a well-diversified portfolio for investors. Therefore, they have attracted the attention of empirical evidence. However, that evidence is scarce for emerging markets and shows heterogeneous results.

Blitz and Huij (2012) examine the performance of ETFs that provide exposure to global emerging market equities finding that there is no convincing evidence that those funds earn higher returns than ETFs which rely on full-replication techniques. Huang and Lin (2011) use optimal asset portfolio procedures and conclude that international diversification is a reasonable strategy. They also show that investing in ETFs is effective for investors because their performance is better than other investing options.

Thanakijsombat and Kongtorarin (2018) review the risk-return characteristics, performance and international diversification benefits of 17 ETFs traded in different emerging markets. They conclude that their performance is poor and that those ETFs are vulnerable to market downturns, therefore, in their opinion, ETFs are ineffective international diversification tools.

In this context of analyzing portfolio performances DEA models are also a useful alternative procedure. Branda (2013) proposes a new efficiency test which is based on traditional DEA models and takes into account portfolio diversification. Cook et al. (2014) suggest that DEA models can be considered to be a tool for multiple-criteria evaluation problems. Liu et al. (2015) show that classic DEA models provide an effective and practical way to approximate the portfolio efficiency.

More recently, Tarnaud and Leleu (2018) provide illustrations to show how their new definition of the technology and the new model orientations could impact efficiency scores and rankings of the portfolios. Finally, Zhou et al. (2018) merge the DEA and the MV approaches to achieve better performances results than the traditional DEA models in the Chinese stock market.

There are more empirical evidence related to the DEA models and portfolio performances, see Solórzano-Taborga et al. (2018) and the Appendix of Tarnaud and Leleu (2018). However, to the best of our knowledge, there are no studies which combine the use of the DEA approach and asset allocation procedures in order to obtain the best portfolio performance neither in emerging markets nor in the way we apply it.

3. Theoretical background

Efficiency and productivity are indicators of success and performance that allow us to evaluate investments. According to Cummins and Zi (1998) the DEA model is a non-parametric approach that allows us to identify and to evaluate the areas of the best performance or best practice within a sample. In other words, the DEA model suggests the best performance within a group of evaluated Decision Making Units (DMU).

The DEA methodology determines efficiency coefficients similar to those obtained by multivariate analysis without any hypothesis of distribution. As it is pointed out by Cummins and Zi (1998), this methodology measures the technical efficiency because it focuses on the input levels related to the outputs. The use of input and output levels is another powerful feature of DEA modelling because it incorporates input and output units without having to be converted to other units. Another important feature of the DEA model is to assign the highest efficiency rating to each DMU relative to the set of DMUs analyzed. The DEA has a low probability of identifying an efficient DMU as inefficient and, although it cannot capture all inefficient units, those identified as inefficient have potential for improvement. Boussofiane et al. (1991) and Dyson et al. (2001) show the technique and the key issues that must be examined on the practical application of the DEA.

The DEA linear programming definitions optimize each individual observation in order to calculate an efficiency frontier determined by the efficient units. These units serve as a reference or benchmark for inefficient units. DEA modelling suggests explicit improvement targets for inefficient DMUs, that is, the border (or reference) point for which it is compared, in order to measure efficiency. This border point is defined as the linear combination of one or more efficient DMUs. The inefficient DMU is presented with a set of efficient DMUs (set of efficient reference DMUs). Changes to improve inefficient DMUs can be determined by analyzing the differences between inefficient DMU and the set of efficient reference DMUs. To identify, in the inefficient DMUs, the excess of consumed inputs or the potential increase of outputs is also another benefit of the DEA.

In accordance with Cooper et al. (2007) the input and output variables for each DMU must obey some criteria:

1. The variables and DMUs must be selected in order to represent the interest of the managers.
2. The numerical values of the input and output variables of each DMU shall be positive.
3. It is preferable to use fewer inputs compared to outputs.
4. The weights for input and output variables of the general DEA model can be determined using the model proposed by Charnes et al. (1978).

There are two classic DEA models: Firstly, the CCR model proposed by Charnes et al. (1978) or CRS (Constant Returns to Scale) model which works with constant returns of scale between inputs and outputs and assumes proportionality between inputs and outputs, and, secondly, the BCC model developed by Banker et al. (1984) or the VRS (Variable Returns to Scale) model which consider variable returns to scale, that is, the proportionality axiom is replaced by the convexity axiom.

The input orientation CCR model is formulated as:

$$\max \Theta = \sum_{r=1}^{m} u_r P_{rk}$$

$$\text{subject to}: \sum_{i=1}^{n} v_i I_{ik} = 1$$

$$\sum_{r=1}^{m} u_r P_{rj} - \sum_{j=1}^{n} v_i I_{ij} \leq 0 \quad j = 1, \ldots, n \tag{1}$$

$$u_r \geq 0$$

$$v_i \geq 0$$

where,

P_{rk} is the amount of output r produced by DMU k (which is being optimized)

I_{ik} is the amount of input i consumed by DMU k

P_{rj} is quantity of output r produced by DMU j

I_{ij} is the amount of input i consumed by DMU j

r represents the number of outputs, r = 1,2, ..., m

i represents the number of inputs, r = 1,2, ..., n

u_r is the weight of output r

v_i is the weight of the input i.

The objective function determines the efficiency of the DMU under analysis, given that the weighted sum of the inputs is equal to 1, according to the first constraint. If Θ <1, DMU k can reduce the amount of inputs consumed by keeping the quantities produced unchanged (inefficiency). The set of inequalities (second constraint) requires that the decision variables u_r and v_i are such that the ratio between the weighted sum of the outputs and the weighted sum of the inputs is at most equal to 1. The third and fourth constraints are of non-negativity. The optimization model seeks to determine the weights for the inputs v_i and for the outputs u_r that maximize the efficiency ranking of the DMU under analysis.

The BCC allows DMUs that use reduced inputs to obtain increasing returns of scale and those that operate with high inputs obtain decreasing returns of scale. These increasing and decreasing returns are verified by the inclusion of a free variable in the model (u_k).

$u_k < 0$ informs decreasing returns,

$u_k > 0$ informs increasing returns, and

$u_k = 0$ informs constant returns.

The BCC model is formulated as:

$$
\begin{aligned}
& \max \Theta = \sum_{r=1}^{m} u_r P_{rk} - u_k \\
& \text{subject to}: \sum_{i=1}^{n} v_i I_{ik} = 1 \\
& \sum_{r=1}^{m} u_r P_{rj} - \sum_{j=1}^{n} v_i I_{ij} \text{ -} u_k \leq 0 \quad j = 1, \ldots, n \\
& u_r \geq 0 \\
& v_i \geq 0
\end{aligned}
\tag{2}
$$

The DEA-CRS and DEA-VRS models are differentiated by the inclusion of the variable u_k that represents the variable returns of scale.

Following Basso and Funari (2001), Haslem and Scheraga (2003), Sengupta (2003), Anderson et al. (2004) and Huang et al. (2015), among others, three inputs (Downside risk, Beta coefficient and Iliquidity) and two outputs (Return rate and Sharpe ratio) were selected.

The first input, downside risk, is selected because its popularity among investors is growing. Grootveld and Hallerbach (1999) point out that one reason for this success is that unlike in standard deviation based risk meters in which all uncertainty is considered to be risky, downside risk measures only consider returns that are below investor's goal to be risky. The global idea behind downside risk is that the left hand side of a return distribution involves risk while the right hand side contains the better investment opportunities. It is calculated as follows:

$$
\text{Downside risk} = \sqrt{\frac{\sum_{i=1}^{n} \left(R_i - R_t \right)^2}{n}} \quad \text{for all } R_i < R_t \tag{3}
$$

where,

n is the number of days in the period under review (one year in our case);

R_i is the asset return;

R_t is the goal return (zero in our case).

The second input, Beta (β), is not a measure of volatility but it shows a fund's correlation to market index. If the beta is smaller than 1 a fund follows markets movements calmly but if the beta is higher than 1 the fund's value even exaggerates market index movements. It is calculated as the ratio between market and ETF covariance and market variance over the whole period.

Finally, the iliquidity ratio reflects the impact of order flow on price, that is, the discount that a seller concedes or the premium that a buyer pays when executing a market order as pointed out by Amihud and Mendelson (1980) and Glosten and Milgrom (1985).

Following previous studies of Amihud (2002) and Acharya and Pedersen (2005), we apply for our empirical analysis the "illiquidity ratio" as the best proxy measure of illiquidity. This ratio is calculated as follows:

$$\text{ILLIQ} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{itd}|}{V_{itd}} \tag{4}$$

where R_{itd} and V_{itd} are, respectively, the return and dollar volume on day *d* in year *t*, and D_{it} is the number of valid observation days in year *t* for stock *i*

On the other hand, the chosen outputs were the return rate, which is computed in this case as the sample mean return and the Sharpe ratio which can be defined as the sample mean of excess returns on the risk-free asset, divided by their sample standard deviation. Following Bessler and Wolff (2015) as risk-free rate we use the yield of a three-month US T-Bill.

$$\text{Sharpe} = \frac{\hat{\mu} - r_f}{\hat{\sigma}} \tag{5}$$

It should not be inferred that the relationship between risk and return is always proportional, that is, if an investor decides to invest with a higher risk there is no guarantee that the return will have the same variation. Then, the DEA model chosen was the DEA-VRS input oriented one, which allows variable returns of scale and risk minimization. The DEA-CRS model was not used in this study because according to Meza and Lins (1998) this model should be adopted when all DMUs operate at optimal scale. Moreover, Rotela Junior et al. (2014) report that the different behaviors of the different sectors of economic activity characterize the existence of variable returns.

The DEA procedure is repeated for every year of the sample in order to define the efficient ETFs for each year. Once defined, those ETFs are considered for computing the allocation weights on each of the two strategies that are considered in this paper. Finally, these weights are used to calculate the portfolio return for the following year. That is the reason why the out-of-sample period is shorter than the whole sample period (that is one year which is the first in-sample period).

As was pointed out, we use two strategies to define the asset allocations. Firstly, we employ the MV portfolio optimization strategy proposed by Markowitz (1952) which is the one that solves:

$$\begin{aligned} &\min \quad \sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \text{Cov}(r_i, r_j) \\ &\text{subject to:} \\ &\sum_{i=1}^{n} w_i = 1 \end{aligned} \tag{6}$$

However, following this strategy, we would consider that investors are exclusively interested in minimizing volatility but it is known that investors are interested not only on minimizing their risks but also on obtaining profits for their investments. Following Bessler and Wolff (2015) and Miralles-Quirós et al. (2019), we opt for considering a second strategy which consists on maximizing the reward-to-risk ratio (Sharpe ratio) or, in other words, maximizing the slope of the Capital Allocation Line (CAL hereafter). This strategy is formulated as follows:

$$\max_{w_t} \quad \frac{w_t' E\{R_{t+1}\} - R_f}{w_t' \; H_{t+1|t} \; w_t}$$

$$\text{subject to:} \qquad (7)$$

$$\sum_{i=1}^{n} w_i = 1$$

Finally, we analyze the performance of the proposed optimal strategies by estimating the out-of-sample Sharpe and Sortino ratios (see Sortino and Satchell, 2001, and Sortino, 2009). The latter is very similar to the former but instead of dividing the excess return by the sample standard deviation is divided by the downside deviation which only considers the excess returns that are below zero.

$$\text{Sortino} = \frac{\hat{\mu} - r_f}{\text{Downside deviation}} \qquad (8)$$

4. Database

We employ in our study daily returns, calculated as natural logarithms between closing prices of two consecutive days, from January 3, 2011 through December 31, 2018 (amounting to 2,017 usable observations) of eighteen emerging markets ETFs. Following the definition of emerging markets given by Morgan Stanley Capital International which was also used by Stevenson (2001), Pavabutr (2003), and Hadhri and Ftiti (2019) we chose those with longer inception dates. As is reported in Table 1, the selected ETFs are from the following countries: Brazil (EWZ), Chile (ECH), Colombia (GXG), Mexico (EWW), and Peru (EPU) from the Americas; Egypt (EGPT), Poland (EPOL), Russia (ERUS), South Africa (EZA), and Turkey (TUR) from Europe, Middle East and Africa; and China (FXI), India (INDY), Indonesia (EIDO), South Korea (EWY), Malaysia (EWM), Philippines (EPHE), Taiwan (EWT), and Thailand (THD) from Asia.

There are two main reasons for employing ETFs. Firstly, ETFs are a portfolio of assets, like mutual funds, but they are also easily traded as a stock. Moreover, ETFs have advantages in terms of intraday liquidity, transparency and fiscal efficiency that mutual funds do not have. Secondly, there is a wide variety of ETFs actively traded on the US stock market that allow investors to reward companies that invest in each country. Table 2 summarizes the descriptive statistics of returns for the different ETFs.

The results indicate that most of the returns are negative but on the basis of the Anova test, we do not reject the null hypothesis that all the return series have the same mean, therefore, those differences are not statistically significant. The higher standard deviation (0.021032) is provided by the ETF related to the Turkish market while the lower one (0.012385) is from the Taiwanese ETF. In this case, the rejection of the null of equality of variances leads us to conclude that differences are statistically significant. All the returns are negatively skewed and present excess kurtosis. Finally, the Jarque–Bera statistic rejects the null hypothesis that the returns are normally distributed in all cases.

Table 1: Emerging Markets ETFs

	Country	Ticker	ETF Name
Americas	Brazil	EWZ	iShares MSCI Brazil ETF
	Chile	ECH	iShares MSCI Chile ETF
	Colombia	GXG	Global X MSCI Colombia ETF
	Mexico	EWW	iShares MSCI Mexico ETF
	Peru	EPU	iShares MSCI Peru ETF
Europe, Middle East & Africa	Egypt	EGPT	VanEck Vectors Egypt Index ETF
	Poland	EPOL	iShares MSCI Poland ETF
	Russia	ERUS	iShares MSCI Russia ETF
	South Africa	EZA	iShares MSCI South Africa ETF
	Turkey	TUR	iShares MSCI Turkey ETF
Asia	China	FXI	iShares China Large-Cap ETF
	India	INDY	iShares India 50 ETF
	Indonesia	EIDO	iShares MSCI Indonesia ETF
	South Korea	EWY	iShares MSCI South Korea ETF
	Malaysia	EWM	iShares MSCI Malaysia ETF
	Philippines	EPHE	iShares MSCI Philippines ETF
	Taiwan	EWT	iShares MSCI Taiwan ETF
	Thailand	THD	iShares MSCI Thailand ETF

5. Empirical results

At this stage, once the yearly inputs and outputs for each DMU have been calculated, we estimate the DEA model yearly in order to determinate the efficient DMUs for each year. We have some cases where some inputs and (or) outputs are negative. This problem is solved by way of the translation invariance property of the VRS models suggested by Ali and Seiford (1990). The results reported in Table 3, where the efficient ETFs are marked with an "X", show the importance of Asian markets because all of them are chosen as efficient markets at least once during the sample period. On the other hand, we observe the scarce efficiency of American emerging markets especially in the period that ranges from 2013 to 2015, which coincides with sharp falls in their quotes, where none of them can be considered to be efficient.

In order to explain the next step of our procedure, we take from Table 3 the results for 2011 where 6 ETFs were considered the efficient: Colombia (GXG), Mexico (EWW), Poland (EPOL), Indonesia (EIDO), South Korea (EWY), and Malaysia (EWM). Their 2011 returns are then used for defining the portfolio weights which optimize the portfolio strategies proposed in this study. Finally, these allocation weights are used to calculate the portfolio returns for the following year (2012 in this example). Therefore, the out-of-sample performance measures that are shown in Table 4 refer to the period which ranges from 2012 to 2018.

Table 2: Descriptive Statistics

	EWZ	ECH	GXG	EWW	EPU	EGPT	EPOL	ERUS	EZA
Mean	-0.000355	-0.000328	-0.000492	-0.000207	-0.000177	-0.000534	-0.000189	-0.000279	-0.000195
Std. Dev	0.019762	0.013145	0.013503	0.014159	0.013375	0.018261	0.017099	0.020278	0.018927
Skewness	-0.406348	-0.065707	-0.170058	-0.574155	-0.490670	-1.013377	-0.515611	-0.588290	-0.262624
Kurtosis	7.209973	8.284391	5.922864	6.731206	13.68378	14.91206	7.678189	7.084278	4.805572
Jarque-Bera	1544.286	2347.133	727.3403	1280.203	9668.927	12264.40	1927.705	1517.516	297.0218

	TUR	FXI	INDY	EIDO	EWY	EWM	EPHE	EWT	THD	Equality Test
Mean	-0.000495	$-5.58 \cdot 10^{-5}$	$5.41 \cdot 10^{-5}$	$-8.40 \cdot 10^{-5}$	$-2.40 \cdot 10^{-5}$	-0.000333	0.000118	$2.52 \cdot 10^{-6}$	0.000117	0.334088 (0.9951)
Std. Dev	0.021032	0.015220	0.014494	0.017223	0.014056	0.013159	0.013283	0.012385	0.014045	80.97109 (0.0000)
Skewness	-0.546467	-0.192604	-0.203284	-0.321286	-0.432707	-6.366765	-0.204000	-0.256485	-0.271523	
Kurtosis	6.744426	5.008282	5.025971	7.017901	6.790424	151.5230	6.155273	4.970062	6.535134	
Jarque-Bera	1278.080	351.2528	358.6678	1390.740	1269.765	1866582.	850.2659	348.1198	1074.534	

This table contains the descriptive statistics for the daily return series for the Emerging Market ETFs for the sample period from January 3, 2011 through December 31, 2018. The last column reports the mean and variance equality tests using the ANOVA and Levene statistics, respectively. Skewness and Kurtosis refer to the series skewness and kurtosis coefficients. The Jarque–Bera statistic tests the normality of the series. This statistic has an asymptotic $\chi^2(2)$ distribution under the normal distribution hypothesis. The p values of these tests are reported in brackets.

Table 3: Efficiency resume from DEA

DATE	EWZ	ECH	GXG	EWW	EPU	EGPT	EPOL	ERUS	EZA	TUR	FXI	INDY	EIDO	EWY	EWM	EPHE	EWT	THD
2011			X	X			X						X	X	X			
2012			X	X		X				X	X				X	X	X	X
2013															X		X	
2014						X					X	X	X			X	X	
2015								X			X					X	X	
2016	X	X			X												X	X
2017		X	X			X	X				X	X		X	X		X	X

Table 4: Out-of-sample performance evaluation

		Data Envelopment Analysis	
	Naïve	**Mean-Variance**	**Capital Allocation Line**
Return (%)	-1.7376476	0.9542042	**3.1846849**
Standard Deviation (%)	16.87741	**14.701565**	20.9040561
Cumulative Return (%)	-12.1704285	6.6832158	**22.3054322**
Sharpe	-0.123149491	0.041723946	**0.136044796**
Sortino	-0.168825628	0.057534418	**0.189891382**

This table contains the out-of-sample performance evaluation of the proposed portfolios based on the annualized mean, annualized standard deviation, cumulative return and annualized Sharpe and Sortino ratios. Best results for returns, standard deviations and Sharpe ratios for each Panel are in bold.

We evaluate the performance of the proposed strategies by comparing their results with those obtained from an equally weighted portfolio (naïve) because, as pointed out by DeMiguel et al. (2009), this strategy is easy to implement because it does not rely either on estimation of the moments of asset returns or on optimization, and because investors continue to use such simple allocation rules for allocating their assets.

We can draw two interesting findings from the results reported in Table 4. Firstly, we observe that both proposed strategies outperform the naïve strategy which yields a negative annualized mean return of -1.73% and a negative cumulative return of -12.17% over the 2012-2018 period. Secondly, the high performance of the CAL strategy must be pointed out. This strategy yields an annualized mean return of 3.18% and a cumulative return of 22.30%, significantly better than the naïve and the MV strategy. Accordingly with the mentioned results, the Sharpe and Sortino performance measures confirm that the best strategy is that of analyzing the efficiency of the emerging markets ETFs using a DEA model and then estimating their allocation weights by using the CAL approach.

Table 5 shows the optimal portfolio weights which optimize the proposed strategies and that were employed for calculating the out-of-sample returns in each year that appears in the table. We observe that Asian markets exhibit the highest allocation weights compared to the rest of the emerging markets. These results support the fact that Asian markets were the only ones to show positive mean returns when descriptive statistics were displayed. On the other hand, we observe that the weights of emerging markets from Europe, Middle East and Africa are smaller than the rest. One possible explanation for these results is provided by Qureshi et al. (2017) who point out that Asian emerging markets are characterized by high profits and are often inclined towards trade and foreign investment. At the same time, European emerging markets tend to underperform their global peers due to rising inflation, depreciating currencies, high interest rates and political turmoil that lead price equities to drop.

6. Robustness test

In order to provide more robustness to our results, we compare the results obtained on the portfolio optimization from the DEA procedure with those obtained from the classical portfolio optimization procedure where all the ETFs are considered for calculating the asset allocation weights. Results are reported in Table 6.

We observe that the fact of defining the efficient ETFs following the DEA approach derives on a clear improvement of the performance measures when compared to those obtained following a naïve procedure or the classical approach of considering the optimization from a set of assets. Higher differences are obtained when the MV strategy is adopted. In these cases, while the naïve and the classical approaches yield negative annualized means and negative cumulative return of -12.17% and -14.41% respectively, the portfolio chosen from a previous DEA approach yields a 6.68% cumulative return. However, the better results are once again obtained when the CAL is applied. In that case, the classical approach produces a cumulative return of 17.24% which is lower than the 22.30% that would be obtained by only considering the efficient assets designed by the DEA procedure. In all cases, the Sharpe and Sortino ratios show that the best portfolio is that which derives from the previous DEA approach.

ETF managers incur on expense ratios (management fees, marketing and operational expenses) that must be taken into account because, as pointed out by Blitz and Huij (2012), the average active fund underperforms the market portfolio by the magnitude of its expenses. In Table 7, we show the results of the out-of-sample portfolio performances considering a 0.59% annual expense ratio (which corresponds with the mean of the expense ratios of the emerging market ETFs considered in this paper).

Table 5: Optimal Portfolio Weights

Panel A: Mean-Variance

Date	EWZ	ECH	GXG	EWW	EPU	EGPT	EPOL	ERUS	EZA	TUR	FXI	INDY	EIDO	EWY	EWM	EPHE	EWT	THD
2012			32,3445												67,6555			
2013			28,7325			8,8048									62,4627			
2014															43,9432		56,0568	
2015						15,0683					4,0727	1,1337				29,0379	50,6875	
2016																52,5396	47,4604	
2017		26,5848			14,1373												21,6483	37,6297
2018			13,9643			14,2416						13,8409			26,5458		2,9911	28,4163

Panel B: Capital Allocation Line

Date	EWZ	ECH	GXG	EWW	EPU	EGPT	EPOL	ERUS	EZA	TUR	FXI	INDY	EIDO	EWY	EWM	EPHE	EWT	THD
2012													99,9988		0,0012			
2013			5,24201			13,1939				36,9863						44,5796		
2014															38,3299		61,6701	
2015												55,8337				44,1663		
2016								99,9989								0,0011		
2017	13,9235				75,0272													11,0493
2018		7,5136				13,5898	14,1254					23,4967		8,1847				33,0898

Table 6: Out-of-sample portfolio performances vs classical approaches

	Naïve	DEA	Classical
Panel A: Mean-Variance			
Return (%)	-1.737647	**0.954204**	-2,058701
Standard Deviation (%)	16.877410	14.701565	**14,684254**
Cumulative Return (%)	-12.170428	**6.683216**	-14,419079
Sharpe	-0.123149	**0.041724**	-0,163406
Sortino	-0.168826	**0.057534**	-0,218839
Panel B: Capital Allocation Line			
Return (%)	-1.737647	**3.184685**	2,462270
Standard Deviation (%)	**16.877410**	20.904056	20,743281
Cumulative Return (%)	-12.170428	**22.305432**	17,245662
Sharpe	-0.123149	**0.136045**	0,102273
Sortino	-0.168826	**0.189891**	0,143025

This table contains in Panels A and B the portfolio performances from solving the Mean-Variance, and Capital Allocation Line strategies respectively. Results Return, Standard deviation and Cumulative returns are reported in percentage. The Naïve column shows the results obtained from an equally weighted portfolio, the DEA one refers to those obtained by selecting previously the ETFs of the portfolio using a DEA approach, and the Classical displays the results of applying the strategies to all the ETFs without considering the previous DEA approach. Best results for each strategy are in bold.

Table 7: Out-of-sample portfolio performances vs classical approaches (with transaction costs)

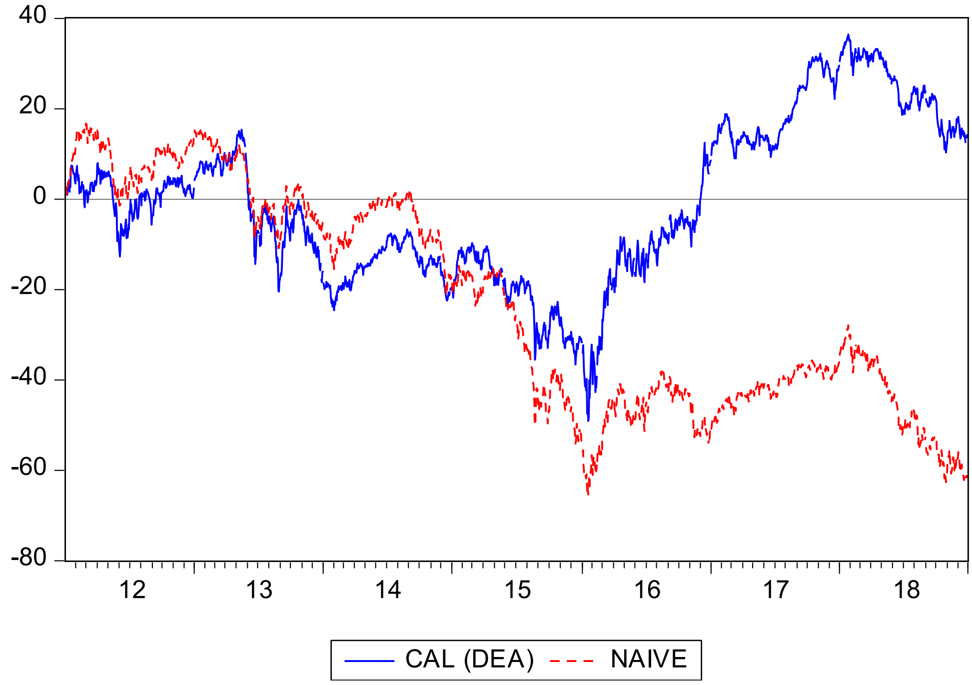
	Naïve	DEA	Classical
Panel A: Mean-Variance			
Return (%)	-8.775757	**-0.386584**	-4.515382
Standard Deviation (%)	16.882131	14.703444	**14,684897**
Cumulative Return (%)	-61.455123	**-2.707622**	-31.625594
Sharpe	-0.540012	**-0.049470**	-0,330692
Sortino	-0.726405	**-0.067938**	-0,439767
Panel B: Capital Allocation Line			
Return (%)	-8.775757	**2.013137**	1.066293
Standard Deviation (%)	16.882131	20.905893	20,745438
Cumulative Return (%)	-61.455123	**14.099948**	7.468281
Sharpe	-0.540012	**0.079994**	0.034971
Sortino	-0.726405	**0.111390**	0.048911

This table contains in Panels A and B the portfolio performances from solving the Mean-Variance, and Capital Allocation Line strategies respectively. Results Return, Standard deviation and Cumulative returns are reported in percentage. The Naïve column shows the results obtained from an equally weighted portfolio, the DEA one refers to those obtained by selecting previously the ETFs of the portfolio using a DEA approach, and the Classical displays the results of applying the strategies to all the ETFs without considering the previous DEA approach. Best results for each strategy are in bold.

The expected drag on returns due to expense ratios leads to obtain negative returns in all cases when the MV strategy is considered. However, returns fall but remain positive when the CAL strategy is applied. Once again, the first-step-DEA approach yields a better performance in terms of annualized mean return, cumulative return, Sharpe and Sortino values when compared to the other two strategies (Naïve and Classical).

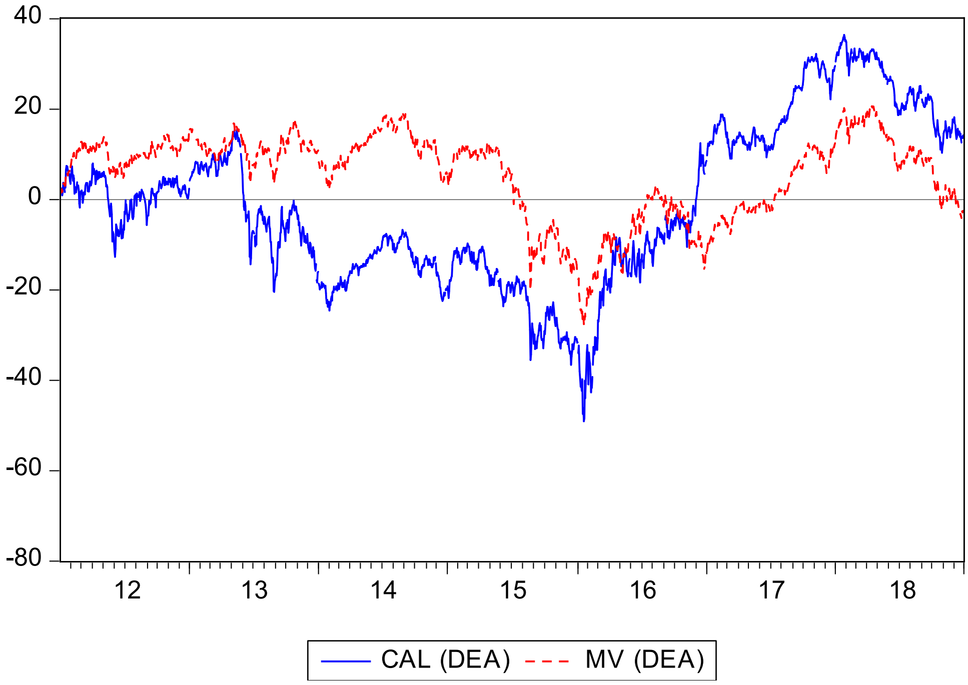
To give additional support to the best performance of the DEA procedure, Figures 1 to 4 display the cumulative returns of the Capital Asset Line strategy after applying the DEA approach compared to the Naïve strategy (Figure 1), the MV strategy also after the DEA approach (Figure 2), and the classical MV and CAL strategies (Figures 3 and 4 respectively).

Figure 1: Cumulative returns of CAL (DEA) strategy vs Naïve



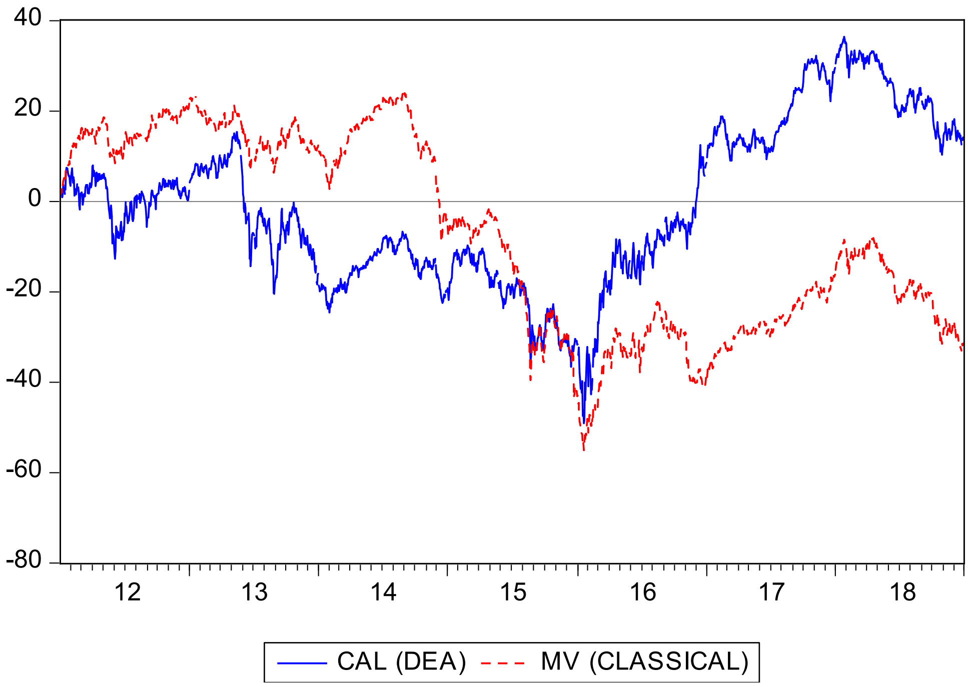
This figure displays the cumulative returns over the out-of-sample period for the naïve rule and the portfolio formed from the Capital Allocation Line (CAL) strategy. The DEA term refers that ETFs in the portfolio were selected in a first step using a DEA approach.

Figure 2: Cumulative returns of CAL (DEA) strategy vs MV (DEA)



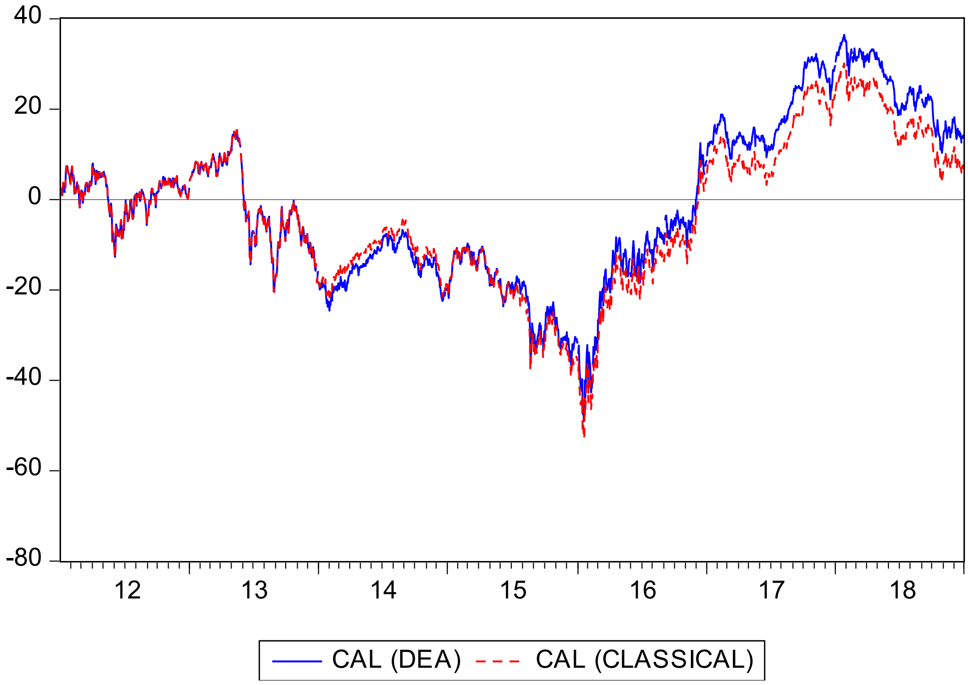
This figure displays the cumulative returns over the out-of-sample period for the Mean-Variance and the Capital Allocation Line (CAL) strategies. The DEA term refers that ETFs in the portfolio were selected in a first step using a DEA approach.

Figure 3: Cumulative returns of CAL (DEA) strategy vs MV (Classical)



This figure displays the cumulative returns over the out-of-sample period for the Mean-Variance and the Capital Allocation Line (CAL) strategies. The DEA term refers that ETFs in the portfolio were selected in a first step using a DEA approach. The Classical term means that the strategy is applied to all the ETFs without considering the previous DEA approach.

Figure 4: Cumulative returns of CAL (DEA) strategy vs CAL (Classical)



This figure displays the cumulative returns over the out-of-sample period for the Capital Allocation Line (CAL) strategies. The DEA term refers that ETFs in the portfolio were selected in a first step using a DEA approach. The Classical term means that the strategy is applied to all the ETFs without considering the previous DEA approach.

We observe that over the entire out-of-sample period the proposed approach produces mostly positive and upward cumulative returns far higher than the rest. Additionally, we find around 2016 a significant upward trend after suffering tough recessions due to a general recovering of portfolio flows to the stock markets and, specifically, to emerging markets.

7. Conclusions

Beside the economic transformation of emerging markets in recent years the investor concerns about their profitability still remain. In order to clarify these concerns, we propose to merge the use of the DEA procedure and two common portfolio strategies, namely the MV and the CAL, using ETFs. The DEA procedure helps investors to identify the efficient ETFs, which link the benefits of mutual funds (because they are portfolios of assets) and equities (they can be transacted at market price anytime during the trading day), and then returns of those ETFs are used for estimating the optimal portfolio allocations for each strategy.

We show that that first step where the DEA approach is used for selecting the ETFs leads investors to outperform not only the naïve strategy but also the classical portfolio optimizations, where all the assets are considered for the optimization estimates, with any of the two strategies that are developed just using the emerging markets selected by the DEA. It is also shown that the CAL strategy which consists of maximizing the reward-to-risk ratio (Sharpe ratio) is the most profitable strategy even when expense ratios are considered.

Additionally, the asset allocation weights show the importance of the Asian emerging markets compared to the rest of emerging markets. We consider that that difference is due to their higher profitability and their inclination towards foreign investment when compared to the European emerging markets which lead price equities to drop during the period 2011-2018.

These results are applicable for individual and institutional investors who can use these techniques to add economic value to their investment strategies.

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