JEL Classification: G10, G11, G14
Keywords: Data Envelopment Analysis, emerging markets, exchange-traded funds, portfolio optimization, performance

Two-Stage Asset Allocation with Data Envelopment Analysis: The Case of Emerging Markets*

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Abstract

Emerging countries have experienced significant geopolitical, economic and demographic changes in recent years. These changes have led investors to doubt the merits of investing in them or not. This study examines different rules of portfolio construction using exchange-traded funds from eighteen emerging markets and employs Data Envelopment Analysis to select the efficient ones. We show that portfolios created using this method clearly outperform equally weighted portfolios and also those built using classical portfolio optimization approaches.

1. Introduction

The transformation of emerging countries as a result of major geopolitical, economic and demographic changes has been remarkable in recent years and has led investors to wonder whether they should invest in these markets. The answer should usually be in the affirmative. However, the fact that their stock markets have shown no net earnings growth for the past eight years (2011–2018)—despite widespread belief among investors that things are changing for the better—means that doubts as to whether or not they can be considered a smart investment option still remain.

This study covers eighteen emerging markets and examines different rules of portfolio construction in order to compare their performance. We improve on previous empirical literature by using exchange-traded funds (hereinafter “ETFs”), which offer an alternative for investors in these markets as passive benchmark indices are tracked on them. These assets are very similar to open-ended funds, but they can be bought and sold at market price anytime throughout the trading day. According to Basu and Huang-Jones (2015), they should be considered as an investment option instead of mutual funds in the absence of superior risk-adjusted returns as they can provide similar diversification opportunities at a lower cost.

* We are most grateful to the editorial team and to two anonymous referees for their helpful comments. This research was funded by Junta de Extremadura under the VI Action Plan for Research and Development 2017/20 through the GIMAF research group (reference GR18022).

https://doi.org/10.32065/CJEF.2020.05.01

Additionally, we suggest using Data Envelopment Analysis (hereinafter "DEA") to select the efficient emerging markets and employing it to estimate asset allocation to 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 area of mutual funds (see Solórzano-Taborga et al., 2018, which 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 combining the use of the DEA method and asset allocation techniques to estimate optimal portfolio weights in emerging markets.

The DEA approach helps to improve the diversification of optimized portfolios as a robust optimization technique because provides an opportunity for researchers to examine risk measures based on generated data and generates cross efficiencies based on financial ratios. We develop the initial DEA concept of an efficient analysis tool that became a popular area in operations research by applying it to asset allocation and, therefore, provide portfolio managers a tool for calculating a more efficient portfolio. Hence, this model is used in this work as a device for isolating victor ETFs from failure ETFs, following an approach that is easy to apply and to understand for practitioners and decision makers. We show that the DEA approach leads to clear performance improvements when compared with classical portfolio optimization models but also with equally weighted portfolios. We obtain mainly positive portfolio performance when the portfolios are built using the DEA method and negative in most of the other cases. It is also interesting to point out that in all portfolio optimization approaches, 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 on emerging markets. Section 3 describes the theoretical background of this paper by explaining the methodology used to create 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 the global economy. Li et al. (2003) used the 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 used the mean-variance framework (hereinafter "MV") and showed that the international diversification benefits remain substantial for US investors if they are subject to short-sale constraints in emerging markets. Different approaches which analyze investment performances of emerging markets were performed by Pavabutr (2003), Gottesman and Morey (2007), Michelson et al. (2008), Lai and Lau (2010) and Basu and Huang-Jones (2015) with heterogeneous behavior, outperforming and underperforming different indices and benchmarks.

In recent years, the spectacular growth in the number of ETFs and their advantages when compared with mutual funds have turned them into an interesting alternative for creating a well-diversified investment portfolio. Therefore, they have attracted some attention in terms of empirical evidence. However, evidence for emerging markets is scarce and shows heterogeneous results as shown by Blitz and Huij (2012), Huang and Lin (2011) and Thanakijsombat and Kongtorarin (2018) who stated that investing in ETFs is effective for investors because their performance is better than other investment options but also that they are vulnerable to market downturns.

In this context of analyzing portfolio performance, DEA models are also useful alternatives. Branda (2013) proposed a new efficiency test, which is based on traditional DEA models and takes into account portfolio diversification. Cook et al. (2014) suggested that DEA models can be considered as tools for multiple-criteria evaluation problems. Liu et al. (2015) showed that classic DEA models provide an effective and practical way to estimate portfolio efficiency.

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

There is more empirical evidence related to DEA models and portfolio performance (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, either in emerging markets or 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 evaluate the areas of 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 (hereinafter DMU).

The DEA methodology determines efficiency coefficients similar to those obtained by multivariate analysis without any hypothesis of distribution. As pointed out by Cummins and Zi (1998), this methodology measures technical efficiency because it focuses on the input levels related to the outputs. The use of input and output levels is another feature of DEA modelling because it incorporates input and output units without the need to have them converted to other units. Another important feature of the DEA model is that it assigns the highest efficiency rating to each DMU in relation 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 show a potential for improvement. Boussofiane et al. (1991) and Dyson et al. (2001) showed the key techniques and issues that must be examined in the practical application of the DEA.

The DEA linear programming definitions optimize each individual observation in order to calculate an efficient 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, i.e., the border (or reference) point with which it is compared in order to measure efficiency. This border point is defined as the linear combination of one or more efficient DMUs. Inefficient DMUs are 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 DMUs and the set of efficient reference DMUs. Another benefit of the DEA is that it can identify the excess of consumed inputs or the potential increase of outputs in inefficient DMUs.

According to Cooper et al. (2007) the input and output variables for each DMU must obey the criteria below:

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 than 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 the CRS (Constant Returns to Scale) model, which works with constant returns to 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 considers variable returns to scale, i.e., the proportionality axiom is replaced by the convexity axiom. Both models are very popular but following Galagedera and Silvapulle (2003), Sengupta (2003), Wilkens and Zhu (2005) and Solórzano-Taborga et al. (2018), among others, we opt for assuming variable returns to scale and then using the BCC model.

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

$u_k < 0$ signifies decreasing returns,

$u_k > 0$ signifies increasing returns,

$u_k = 0$ signifies constant returns,

The formula for the input-oriented BCC (VRS) model is as follows:

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

where,

Θ is the efficiency score for the DMU

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 the amount 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, i = 1,2, ..., n

u_r is the weight of output r

v_i is the weight of the input i.

We follow an input-oriented BCC (VRS) model because it measures the efficiency of outputs over inputs, placing emphasis on reduction of certain inputs to improve efficiency. As a consequence, an input-oriented model will reduce inputs with a constant outputs level. It should not be inferred that the relationship between risk and return is always proportional, that is, if an investor decides to invest at 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 for variable returns to scale and risk minimization. The DEA-CRS model was not used in this study because according to Meza and Lins (1998), this model should only be adopted when all DMUs operate at optimal scale. Moreover, Rotela Junior et al. (2014) reported that the different behaviors of the different sectors of economic activity characterize the existence of variable returns.

We have chosen risk measures (downside risk, beta coefficient and Amihud illiquidity ratio) as inputs and return measures (rate of return and Sharpe ratio) as outputs. We based our variable selection on historical evidence, following Basso and Funari (2001), Haslem and Scheraga (2003), Sengupta (2003), Anderson et al. (2004), Huang et al. (2015) and Tarnaud and Leleu (2018), among others, but also on objective judgement where we found two main reasons for choosing these variables. Firstly, these inputs and outputs correspond to the activities of portfolio holders for the analysis to make sense. Secondly, these measures are chosen because higher output values and lower input values indicate better performances.

Relative to the first input, downside risk, we follow those ratios that use lower partial moments, LPMs, to measure risk. This measure, which was first proposed by Bawa and Lindenberg (1977), consider only negative deviations of returns from a minimal acceptable return or threshold. This is different to standard deviation which considers both positive and negative deviations from the expected return.

$$LPM_{xA}(\tau) = \frac{1}{T}\sum_{t=1}^{T}\max\left[\tau - \mu_{At}, 0\right]^{x} \qquad (2)$$

where τ is the minimum acceptable return (zero in our case) and x is the order of the lower partial moment which can be interpreted, in accordance with Eling and Schuhmacher (2007), as the investor's risk attitude. Therefore, a lower partial moment order of 0<x<1 is appropriate for risk-seeking investors; a lower partial moment order of 1 is the expected shortfall (for risk-neutral investors) and a lower partial moment order of 2 is the downside risk (appropriate for risk-averse investors). Therefore, downside risk is calculated as:

$$\text{Downside risk} = \frac{1}{T}\sum_{t=1}^{T}\max\left[\tau - \mu_{At}, 0\right]^{2} \tag{3}$$

Grootveld and Hallerbach (1999) pointed out that one reason for the success of downside risk is that unlike standard deviation-based risk meters in which all uncertainty is considered to be risky, downside risk only considers returns that fall below an investor's target to be risky. That statement confirms Markowitz's (1991) assertion which stated that returns above the mean can hardly be regarded as risky by investors, but the variance below the mean provides more information during extreme market events. This fact leads us to confirm that investors worry more about underperformance than overperformance. Finally, Gilmore et al. (2005) pointed out that downside risk measures become preferable to help investors make proper optimization decisions.

The second input, beta (β), is a measure of an asset's volatility in relation to the market. It essentially measures the relative risk exposure of holding a particular stock or sector in relation to the market. If the beta is smaller than 1, a fund follows market movements calmly but if the beta is higher than 1, the fund's value exaggerates market index movements. This is calculated as the ratio between market and ETF covariance and market variance over the whole period. We have employed the SPY ETF, which tracks the S&P500 index, as the benchmark reference.

Finally, the illiquidity ratio reflects the impact of order flow on price, that is, the discount that a seller gives 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 the previous studies by Amihud (2002) and Acharya and Pedersen (2005), we used the "illiquidity ratio" as the best proxy illiquidity measure for our empirical analysis. This ratio is calculated as follows:

$$\text{ILLIQ} = \frac{1}{D_{At}}\sum_{d=1}^{D_{At}}\frac{\left|R_{Atd}\right|}{V_{Atd}} \tag{4}$$

where R_{Atd} and V_{Atd} are, respectively, the return and dollar volume on day d in period t, and D_{At} is the number of valid observation days in period t for stock A

On the other hand, the chosen outputs were the rate of return, 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), we used the yield of a three-month US T-Bill as the risk-free rate.

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

It must be pointed out that it is not necessary for these variables to be under the control of managers because several DEA methods, which include the Charnes et al. (1981) approach, the categorical model proposed by Banker and Morey (1986a), the discretionary model derived by Banker and Morey (1986b) and the two-stage method, used in this study, described by Pastor (2002) and Coelli et al. (2005), accommodate such variables.

In our two-stage approach, the DEA procedure was repeated in the first stage for each year of the sample in order to define the efficient ETFs for each year. Once these ETFs are defined, the second stage of this approach begins when these ETFs are taken into account to compute the allocation weights on each of the two strategies considered in this paper. Finally, these weights were used to calculate the portfolio return for the following year. This is the reason why the out-of-sample period was shorter than the whole sample period (i.e. one year, which is the first in-sample period).

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

$$\min \quad \sigma_p^2 = \sum_{A=1}^{n}\sum_{B=1}^{n} w_A w_B \mathrm{Cov}\left(r_A, r_B\right) \quad \text{subject to:} \quad \sum_{A=1}^{n} w_A = 1 \tag{6}$$

However, this strategy only considers investors to be exclusively interested in minimizing volatility despite the fact that investors are usually interested not only in minimizing their risks but also in profiting from their investments. Following Bessler and Wolff (2015) and Miralles-Quirós et al. (2019), we chose to consider a different strategy, which consists in maximizing the reward-to-risk ratio (Sharpe ratio) or, in other words, maximizing the slope of the Capital Allocation Line (hereinafter "CAL"). The formula for this strategy is as follows:

$$\max_{w_t} \quad \frac{w' E\left\{R_{t+1}\right\} - R_f}{w' \; H_{t+1|t} \; w} \qquad \text{subject to:} \; \sum_{A=1}^{n} w_A = 1 \tag{7}$$

Finally, we analyzed 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, which was suggested by Sortino and van der Meer (1991), is very similar to the former but instead of dividing the excess return by the sample standard deviation, it is divided by the downside deviation, which only considers excess returns below zero.

$$\text{Sortino} = \frac{\hat{\mu} - r_f}{\sqrt{LPM_{2A}\left(\tau\right)}} \tag{8}$$

4. Database

Our study made use of daily returns, calculated as natural logarithms between the closing prices on two consecutive days, from January 3, 2011 to 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. Table 1 reports the selected ETFs and Table 2 summarizes the descriptive statistics of returns for the different ETFs.

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, the 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

Results indicated that most of the returns were negative. The higher standard deviation (0.021032) comes from the ETF related to the Turkish market while the lower one (0.012385) is from the Taiwanese ETF. All the returns were negatively skewed and presented excess kurtosis. Finally, the Jarque–Bera test rejected the null hypothesis that the returns are normally distributed in all cases.

Relative to the correlations among inputs and outputs, Eling (2006) stated that inputs and outputs should differ from one another as far as possible in order to determine a great explanatory power. Correlations of inputs and outputs for the whole period are given in Table 3.

Table 2 Descriptive Statistics

	EWZ	*ECH*	*GXG*	*EWW*	*EPU*	*EGPT*	*EPOL*	*ERUS*	*EZA*
Mean	$-3.55 \cdot 10^{-4}$	$-3.28 \cdot 10^{-4}$	$-4.92 \cdot 10^{-4}$	$-2.07 \cdot 10^{-4}$	$-1.77 \cdot 10^{-4}$	$-5.34 \cdot 10^{-4}$	$-1.89 \cdot 10^{-4}$	$-2.79 \cdot 10^{-4}$	$-1.95 \cdot 10^{-4}$
Std. Dev	0.019	0.013	0.013	0.014	0.013	0.018	0.017	0.020	0.018
Skewness	-0.406	-0.065	-0.170	-0.574	-0.490	-1.013	-0.515	-0.588	-0.262
Kurtosis	7.209	8.284	5.922	6.731	13.683	14.912	7.678	7.084	4.805
Jarque-Bera	1544.286	2347.133	727.340	1280.203	9668.927	12264.40	1927.705	1517.516	297.021

Table 2 Descriptive Statistics (Continued)

	TUR	FXI	INDY	EIDO	EWY	EWM	EPHE	EWT	THD
Mean	$-4.95 \cdot 10^{-4}$	$-5.58 \cdot 10^{-5}$	$5.41 \cdot 10^{-5}$	$-8.40 \cdot 10^{-5}$	$-2.40 \cdot 10^{-5}$	$-3.33 \cdot 10^{-4}$	$1.18 \cdot 10^{-4}$	$2.52 \cdot 10^{-6}$	$1.17 \cdot 10^{-4}$
Std. Dev	0.021	0.015	0.014	0.017	0.014	0.013	0.013	0.012	0.014
Skewness	-0.546	-0.192	-0.203	-0.321	-0.432	-6.366	-0.204	-0.256	-0.271
Kurtosis	6.744	5.008	5.025	7.017	6.790	151.523	6.155	4.970	6.535
Jarque-Bera	1278.080	351.252	358.667	1390.740	1269.765	1866582	850.265	348.119	1074.534

Table 3 Correlation Matrix of Inputs and Outputs

	DOWNSIDE RISK	*BETA*	*ILLIQUIDITY*	*RETURN*	*SHARPE*
DOWNSIDE RISK	1				
BETA	0.4943	1			
ILLIQUIDITY	0.4693	-0.3836	1		
RETURN	-0.5051	0.2299	-0.5640	1	
SHARPE	-0.2950	-0.0304	-0.0668	0.3292	1

Notes: This table contains the descriptive statistics for the series of daily returns for the Emerging Markets ETFs for the sample period from January 3, 2011 to December 31, 2018. Skewness and Kurtosis refer to the series skewness and kurtosis coefficients. The Jarque–Bera Test tests for the normality of the series. This statistic has an asymptotic $\chi^2(2)$ distribution under the normal distribution hypothesis.

5. Empirical Results

At this stage, once the yearly inputs and outputs for each DMU were calculated, we estimated the DEA model on an annual basis in order to determine the efficient DMUs for each year. We had some cases where some inputs and (or) outputs were negative. This problem was solved by way of the translation invariance property of the VRS models suggested by Ali and Seiford (1990). The results reported in Table 4, where the efficient ETFs are marked with an “X”, show the importance of Asian markets because all of them were chosen as efficient markets at least once during the sample period. On the other hand, we observed the low efficiency of the emerging markets from the Americas, especially in the period that ranged from 2013 to 2015. This coincides with sharp drops in their quotes, and none of them can be considered to be efficient.

In order to explain the next step in our procedure, we took from Table 4 the results for 2011 where six ETFs were considered to be efficient: Colombia (GXG), Mexico (EWW), Poland (EPOL), Indonesia (EIDO), South Korea (EWY), and Malaysia (EWM). Their 2011 returns were then used to define the portfolio weights optimizing the portfolio strategies proposed in this study. Finally, these allocation weights were 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 5 refer to the period ranging from 2012 to 2018.

With the aim of reinforcing the benefits of using a two-stage asset allocation procedure, labeled as 2-Stage, we compare the performance of the proposed strategies with those obtained from the classical portfolio optimization procedure, labeled as Classical, where all the ETFs are considered in calculating the asset allocation weights. In both cases, we also consider 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 on either 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 drew interesting findings from the results reported in Table 5. Firstly, we observed that defining the efficient ETFs following the two-stage asset allocation approach results in a clear improvement of the performance measures when compared to those obtained following a classical procedure. There is a clear improvement of mean return when results from the classical and two-stage procedures are compared. On the other hand, standard deviations are not improved when the two-stage asset allocation is applied in all the strategies but it has no influence on the performance measures due to the clear improvement of the mean returns in all cases.

Secondly, the greatest differences in terms of cumulative returns were obtained when the MV strategy was adopted. In this case, while the classical approach yielded a negative cumulative return of -14.419% the portfolio chosen using a preliminary DEA approach yielded a 6.683% cumulative return. On the other hand, smaller differences between the classical and the two-stage asset allocation procedures were obtained when the Capital Allocation Line strategy was applied. In this case, the classical approach produced a cumulative return of 17.24%, which is lower than the 22.30% that would have been obtained if only the efficient assets designed by the DEA procedure were considered. In both cases the naïve approach was also outperformed.

Finally, we must state that the Capital Allocation Line is the best strategy once analyzed the Sharpe and Sortino ratios. We observe that the values of these ratios when the two-stage asset allocation is employed (0.136 and 0.189 respectively) clearly outperform those obtained when the Mean-variance approach is considered (0.041 and 0.057 respectively) but also those obtained by using the classical and the naïve approaches, which are even negative in some cases. In accordance with the aforementioned results, the Sharpe and Sortino performance measures confirmed that the best strategy was 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 6 shows the optimal portfolio weights that optimize the proposed strategies and that were employed for calculating the out-of-sample returns for each year that appears in the table. We observed that Asian markets exhibited the highest allocation weights compared with the rest of the emerging markets. These results support the fact that Asian markets were the only ones that showed positive mean returns when descriptive statistics were displayed. On the other hand, we observed that the weights of emerging markets from Europe, the Middle East and Africa were smaller than the rest. One possible explanation for these results was provided by Qureshi et al. (2017), which pointed 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.

Table 4 Summary of Efficiency 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 5 Out-of-Sample Portfolio Performances 2-stage Asset Allocation vs. Classical Approach

	Classical			*2-Stage*		
	Naïve	***MV***	***CAL***	***Naïve***	***MV***	***CAL***
Return (%)	-1.737	-2.058	2.462	**0.173**	**0.954**	**3.184**
Standard Deviation (%)	**16.877**	**14.684**	**20.743**	17.778	14.701	20.904
Cumulative Return (%)	-12.170	-14.419	17.245	**1.218**	**6.683**	**22.305**
Sharpe	-0.123	-0.163	0.102	**-0.009**	**0.041**	**0.136**
Sortino	-0.168	-0.218	0.143	**-0.012**	**0.057**	**0.189**

Notes: This table shows portfolio performances after applying the Naïve, Mean-Variance (MV) and Capital Allocation Line (CAL) strategies, respectively. The return of results, standard deviation and cumulative return are reported as percentages. The Classical columns list the results from applying the strategies to all the ETFs without considering a preliminary DEA approach, and the 2-Stage ones refer to those obtained by selecting the portfolio's ETFs beforehand using a DEA approach. The best results for each measure are in bold.

Table 6 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 7 Out-Of-Sample Portfolio Performances 2-Stage Asset Allocation vs. Classical Approach (Including Transaction Costs)

	Classical			*2-Stage*		
	Naïve	***MV***	***CAL***	***Naïve***	***MV***	***CAL***
Return (%)	-8.775	-4.515	1.066	**-0.997**	**-0.386**	**2.013**
Standard Deviation (%)	**16.882**	**14.684**	**20.745**	17.780	14.703	20.905
Cumulative Return (%)	-61.455	-31.625	7.468	**-6.987**	**-2.707**	**14.099**
Sharpe	-0.540	-0.330	0.034	**-0.075**	**-0.049**	**0.079**
Sortino	-0.726	-0.439	0.048	**-0.103**	**-0.067**	**0.111**

Notes: This table shows portfolio performances after applying the Naïve, Mean-Variance (MV) and Capital Allocation Line (CAL) strategies, respectively and transaction costs. The return of results, standard deviation and cumulative return are reported as percentages. The Classical columns list the results from applying the strategies to all the ETFs without considering a preliminary DEA approach, and the 2-Stage ones refer to those obtained by selecting the portfolio's ETFs beforehand using a DEA approach. The best results for each measure are in bold.

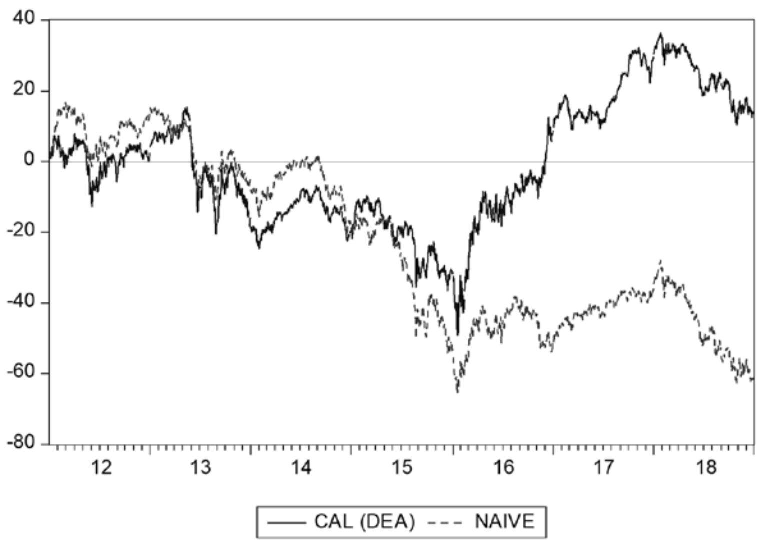
6. Robustness Test

ETF managers incur expense ratios 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 out-of-sample portfolio performance considering a 0.59% annual expense ratio (which corresponds with the mean of the expense ratios from the emerging markets ETFs considered in this paper).

The expected drag on returns due to expense ratios led to negative returns in all cases when the Naïve and MV strategies were considered. However, returns fell but remained positive when the CAL strategy was applied. In this case, we observe that the Cumulative Return using the two-stage procedure (14.099%) is twice as much as the one obtained using the classical approach (7.468%). Relative to the Sharpe and Sortino ratios, we obtain values of 0.079 and 0.111 respectively using the proposed two-stage asset allocation approach which clearly outperform those obtained using the classical procedure (0.034 and 0.048 respectively) where the DEA model was not taken into account. Once again, the two-stage asset allocation approach yielded a better performance in terms of annualized mean return, cumulative return, Sharpe and Sortino values when compared to the classical strategy.

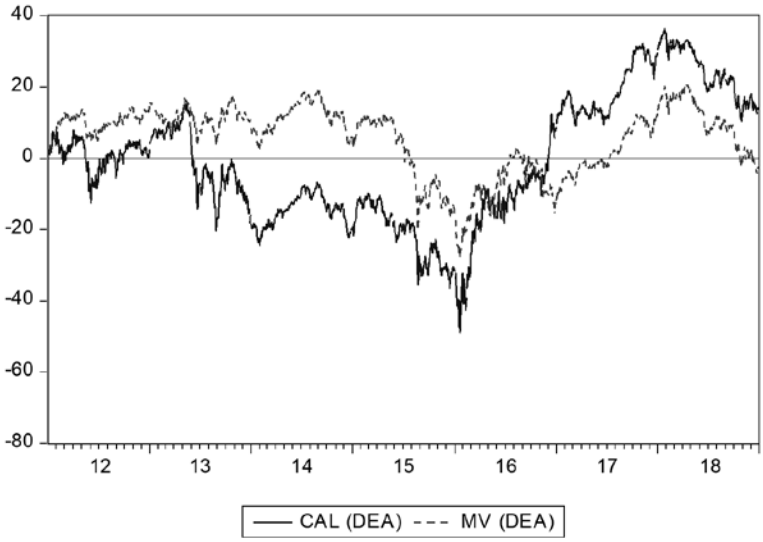
As additional support for better performance after using the DEA procedure, Figures 1 to 4 show the cumulative returns of the Capital Asset Line strategy after applying the DEA approach as compared with the Naïve strategy (Figure 1), the MV strategy after likewise applying the DEA approach (Figure 2), and the classical MV and CAL strategies (Figures 3 and 4, respectively).

Figure 1 Cumulative Returns of the CAL (DEA) vs. Naïve Strategies



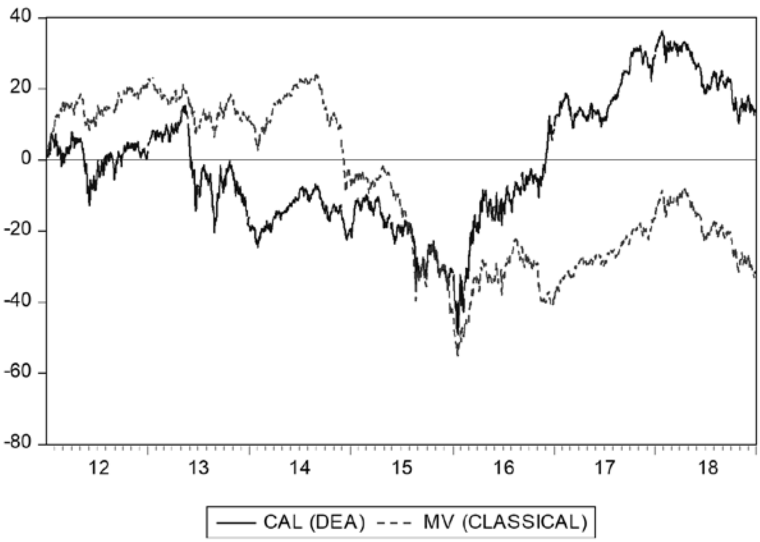
Notes: This figure shows the cumulative returns over the out-of-sample period for the naïve rule and the portfolio built using the Capital Allocation Line (CAL) strategy. The term DEA refers to the fact that the portfolio's ETFs were selected beforehand using a DEA approach.

Figure 2 Cumulative Returns of the CAL (DEA) vs. MV (DEA) Strategies



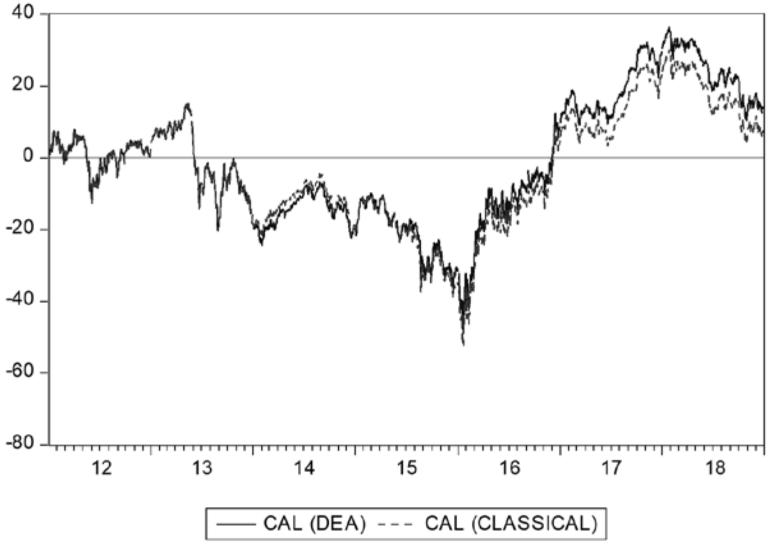
Notes: This figure shows the cumulative returns over the out-of-sample period for the Mean-Variance and the Capital Allocation Line (CAL) strategies. The term DEA refers to the fact that the portfolio's ETFs were selected beforehand using a DEA approach.

Figure 3 Cumulative Returns of the CAL (DEA) vs. MV (Classical) Strategies



Notes: This figure shows the cumulative returns over the out-of-sample period for the Mean-Variance and the Capital Allocation Line (CAL) strategies. The term DEA refers to the fact that the portfolio's ETFs were selected beforehand using a DEA approach. The term Classical means that the strategy has been applied to all the ETFs without considering a preliminary DEA approach.

Figure 4 Cumulative Returns of the CAL (DEA) vs. CAL (Classical) Strategies



Notes: This figure shows the cumulative returns over the out-of-sample period for the Capital Allocation Line (CAL) strategies. The term DEA refers to the fact that the portfolio's ETFs were selected beforehand using a DEA approach. The term Classical means that the strategy has been applied to all the ETFs without considering a preliminary DEA approach.

We observed that over the entire out-of-sample period, the proposed approach produced mostly positive and upward cumulative returns that are much higher than the rest. Additionally, around 2016, we found a significant upward trend after a tough recession hit. Portfolio flows to the stock markets and, specifically, to emerging markets, generally recovered.

7. Conclusions

Despite the economic transformation of emerging markets in recent years, investor concerns about their profitability still remain. In order to dispel these concerns, we sought to merge the DEA procedure with two common portfolio strategies, namely the MV and the CAL, using ETFs. The DEA procedure helps investors identify efficient ETFs, linking the benefits of mutual funds (because they are portfolios of assets) and equities (they can be bought and sold at market price anytime throughout the trading day). The returns of these ETFs are then used to estimate the optimal portfolio allocations for each strategy.

We showed that by including an initial step where the DEA approach is used to select the ETFs, investors are able to outperform not only the naïve strategy but also the classical portfolio optimization approaches. All the assets are considered for the optimization estimates, with either of the two strategies developed only using the emerging markets selected by the DEA. It has also been shown that the CAL strategy, which consists in 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 Asian emerging markets compared with the rest of the emerging markets. We believe that such a difference is due to their higher profitability and their inclination towards foreign investment when compared to European emerging markets, which led price equities to drop during the 2011–2018 period.

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

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