Efficiency of mutual funds in Croatia: a DEA-based approach applied in the pre-crisis, crisis and post crisis period

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Abstract. The aim of this paper is to estimate the overall performance of mutual funds in Croatia in terms of their relative efficiency based on several performance indicators using data envelopment analysis (DEA). DEA is a non-parametric method that can provide an overall relative efficiency score of a certain fund given a number of risk, cost or reward or profitability measures. Since traditional mutual fund performance indicators are mostly based on the CAPM paradigm that demands using rigid assumptions and questionable benchmarks, we endeavor to overcome the limitations of such an approach by considering more appropriate risk and reward measures, such as Expected Shortfall, stochastic dominance and higher order moments. In this way, we developed an adjusted DEA-based mutual fund performance index. The efficiency scores obtained from the DEA model help in identifying efficient funds and ranking the funds based on certain criteria. DEA also identifies mutual fund(s) that can be benchmarks for other mutual funds that have similar investment strategies. These results were compared to various traditional indicators of absolute and relative risk-adjusted performance of mutual funds. The analysis was divided into three periods: the pre-crisis period, crisis period and post-crisis period with different conclusions for mutual fund performances in Croatia. The analysis includes altogether 60 UCITS funds in Croatia, in the period from the beginning of 2005 until the end of 2015, and was conducted on daily data of share prices, available from the Bloomberg terminal.

Keywords: institutional investors, data envelopment analysis, mutual fund performance, DEA mutual fund performance indexes, Croatia

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1. Introduction

Mutual funds are an important investment vehicle for retail and institutional investors on developed financial markets. They are also one of the largest instituti-

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onal investors and asset managers, and exert a significant impact on the liquidity and activity of financial markets. This ranges from voluntary pension savings of households to risky investment approaches in the case of aggressive equity funds. By the end of 2014, the importance of mutual funds, measured as a share of total asset in the financial sector ranges from 21.8% in the USA [7], 18.8% in the Euro zone [14] to only 2.7% in Croatia [11]. Mutual funds can differ in organisational framework and legal treatment, but mostly they differ due to their investment strategy. These include money market funds, bond funds, balanced and equity funds. In Croatia, the regulatory framework differentiates two types of mutual funds: UCITS (Undertakings for Collective Investment in Transferable Securities) – open-end investment funds with public offerings, and AIF – Alternative Investment Funds. According to UCITS Directives, UCITS funds (the subject of this paper) are mutual funds operating on a single financial services market in the European Union. The first UCITS Directive was adopted in 1985, and the last amendments were made in 2014, resulting in the current UCITS V Directive. These directives have been transposed into Croatia's legal framework. At the end of 2015, total net assets of mutual funds in Europe were 12,581 billion EUROs, with 65% of these assets attributed to UCITS investment funds, while the rest were nationally regulated funds or other types of mutual funds (AIF and other non-UCITS). The dominant form of mutual funds by investment strategy in the European Union was equity funds, followed by bond funds, balanced funds and finally money market funds [15]. The financial crisis has had a significant impact on UCITS funds in the European Union. In 2008, total net assets of UCITS funds were reduced by 26.4%, while net outflows were 356 billion EUROs [18].

At the end of 2015, the total net assets of mutual funds on the Croatian market were 2,194 mil. EUROs. UCITS funds accounted for 82.7% of total net assets of mutual funds. Money market funds were the dominant form of UCITS funds with net assets accounting for 66.8%, 11.8% for equity funds, 10.5% for bond funds, 5.8% for balanced funds and 5.1% for others types of funds [10]. The financial crisis has had a severe impact on mutual funds in Croatia, as is evident in the huge outflows, negative returns and the subsequent crash in net assets. This impact is still present in the Croatian market of mutual funds, where net assets have not yet recovered to pre-crisis values, unlike European Union countries.

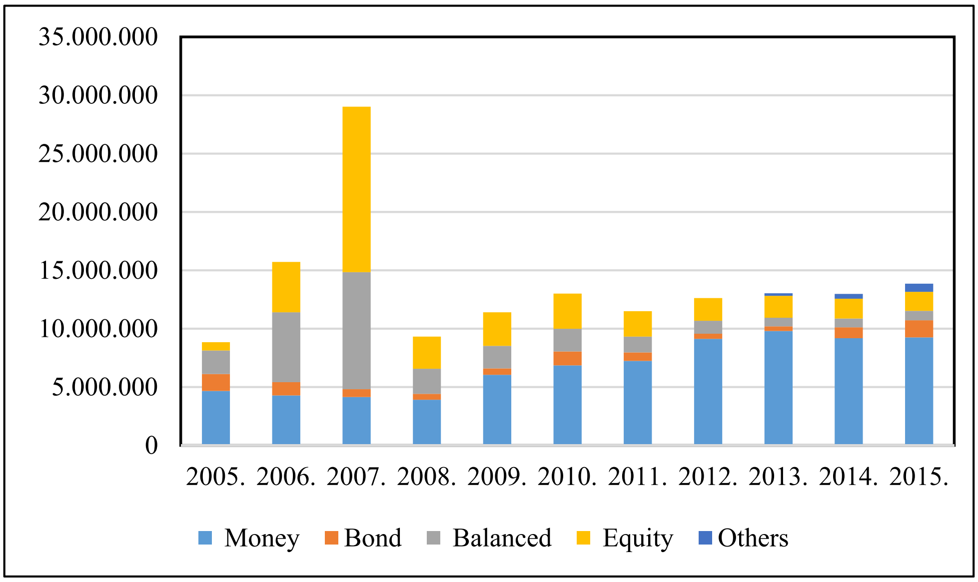

Figure 1: *Net assets of UCITS funds at the end of period, in thousands of HRK [10]*

The beginning of the financial crisis in Croatia was evident on 15 November 2007, when the Zagreb Stock Exchange equity index (CROBEX) had lost 9 percent in one month. This was the beginning of a 77 percent decline over a period of one and a half years. On 9 March 2009, CROBEX hit rock bottom at 1,263 points [16]. We used these two dates to divide our research in three periods: the pre-crisis period ($T1$: 1/1/2005 – 15/11/2007), crisis period ($T2$:16/11/2007 – 9/3/2009) and post-crisis period ($T3$:10/3/2009 – 31/12/2015).

Therefore, the aim of this paper is to estimate the overall performance of mutual funds in Croatia during these three periods based on several performance indicators and in terms of their relative efficiency. The traditional approach to analysing the performance of mutual funds relies mostly on CAPM-based indicators following rigid assumptions and questionable benchmarks. Therefore, we have endeavoured to overcome these limitations by considering a set of appropriate risk and reward measures that provide more informative overall performance of funds. For this purpose, data envelopment analysis (DEA) was used. DEA is a non-parametric method that gives an overall relative efficiency score of a certain entity based on several (risk, cost, reward or profitability) measures. This methodology is generally accepted for evaluating the performance of mutual funds. Accordingly, an overview of the previous research is given in Section 2, and subsequently, the empirical DEA model is elaborated in Section 3. The results from the DEA model are presented and interpreted in Section 4. Section 5 presents our conclusions stemming from an analysis of the relative efficiency of funds during the three respective periods, including the detected benchmark funds and their peer groups. Finally, the DEA and Information ratio rankings are compared.

2. Previous research review

The methodological framework for measuring profitability of mutual funds has been well developed. Besides traditional risk and return measures, the methodological framework includes absolute and relative risk-adjusted performance measures which allow a better comparison of funds. Some of the most prominent absolute risk-adjusted performance measures are: Sharpe ratio, Treynor ratio and VaR-based measures. Examples of relative risk-adjusted performance measures are evident in the use of Jensen's alpha, Information ratio, M^2 measure, Graham-Harvey measures and the Sortino ratio [1:84-87].

The DEA methodology is often applied in measuring the relative performance of mutual funds. One of the first attempts to do so was by Murthi et al. [26] who developed the mutual fund performance index (DPEI) using the DEA methodology. They considered the return as output and the standard deviation and transaction costs as inputs. The DPEI index was further researched and developed by Basso and Funari [4], including stochastic dominance as output. Kuosmanen [19] proposed a method for measuring the performance of funds and best practices benchmarking, which compares the mutual fund performance to an endogenously selected benchmark portfolio that tracks the evaluated fund's risk profile. This paper uses DEA to model an investment universe, where the risk profile of a mutual fund is also characterized by means of stochastic dominance criteria. Lean, Phoon, Wong [22] use only stochastic dominance criteria to evaluate CTA funds. Also, Lozano and Gutirrez [24] proposed six distinct DEA-like linear programming (LP) models for computing relative efficiency scores consistent with second-order stochastic dominance in order to detect the optimal benchmark portfolio for any rational risk-averse investor. Lamb and Tee [20] use DEA to identify the returns to scale and measures needed for a DEA model of mutual funds and show how to handle scope for diversification. In another paper, Lamb and Tee [21] further investigate the application of DEA for comparing investment funds and develop stochastic DEA models for funds, derive confidence intervals, develop techniques to compare and rank funds and represent the ranking and consider autocorrelation in time series. Empirical research using the DEA methodology has been conducted not just for predominantly US mutual funds, but also Italian, Greek, Chinese mutual funds.

The DEA methodology has also been applied for analysing the efficiency of different types of mutual funds. Prominent research has been conducted for the case of socially responsible mutual funds. Perez-Gladish et al. [28] analysed the efficiency of mutual funds subject to financial and social responsibility criteria using data envelopment analysis consistent with second-order stochastic

dominance efficiency. Basso and Funari [5] analysed the performance of socially responsible investment (SRI) funds using various proposed DEA models, which differ in the way the ethical objective is taken into account. The paper by Guo, Ma, Zhou [17] used the input-oriented BCC model to evaluate the performance of 27 open-end funds in the 2010, and took into account the investment cost and moments of higher order.
Recent research by Banker et al. [3] conducted additive data envelopment analysis (DEA) focusing on risk-adjusted returns during different time periods as trade-level outcomes. They analysed a trade-level measure of the efficiency of fund managers in buying and selling transactions and the determinants of fund managers trading performance. A relevant research topic is the size and performance of a fund. Basso and Funari [6] discussed the role of fund size in the performance evaluation and analysed the appropriateness of including information on size among the input/output variables in DEA. They also studied the presence of the relationship between performance scores and the size of mutual funds for a set of European equity mutual funds. In addition, they also considered scale efficiency and investigated whether the analysed funds exhibit constant, increasing or decreasing returns to scale.
Research on the application of absolute and relative risk-adjusted performance measures for UCITS funds in Croatia has been conducted by Ćurković and Krišto [12]. They analysed 55 UCITS funds in Croatia for the period 2011-2014. They concluded that funds with higher assets values outperformed funds with below-average assets values which were also more volatile, based on the Sharpe and Information ratio. At the same time, funds under foreign-owned management companies were more successful than funds under domestically-owned management companies, but these latter funds also had higher standard deviation [12].

3. Methodology

Our analysis uses DEA to select DEA-efficient decision-making units (DMUs) subject to certain criteria. DEA applies mathematical programming to assess the relative efficiency of certain (homogeneous) entities, called decision-making units, using empirical data on their inputs and outputs [25:21]. Roughly speaking, the most DEA-efficient unit is that which has a relatively greater ratio of weighted outputs to weighted inputs compared to other units in the observed set [29:23].
In this analysis, the DMUs are the UCITS funds in Croatia. To choose the appropriate comparison criteria, the assumption is that the decision makers (investors) prefer greater return and positive skewness [23:84] and are risk averse in terms of downside volatility and probability of loss. Measures chosen to describe these preferences in the analysis are average return, coefficient of skewness, semi-variance, *Expected Shortfall* (or CVaR) and the indicator of the stochastic non-

dominance. The indicator of stochastic non-dominance is evaluated as the greatest degree of SD according to which a fund belongs to SD-efficient funds up to the third degree stochastic dominance criteria and the Davidson and Duclos test [13]. Following the reasoning behind a production process, the indicators preferred to have a greater value are treated as outputs, and the indicators with preferably small values are treated as inputs in DEA. Therefore, chosen output variables are the excess return, skewness and SD, while chosen inputs are semi-variance and *Expected Shortfall* (*ES*). Given that the output values (return and skewness) can be negative, and DEA models (and solvers) are developed for nonnegative data, it was necessary to transform this data to nonnegative values and use a model that is invariant to the transformation of outputs. The input-oriented BCC model [2] was found to meet those requirements [27], so it was used in the analysis. The BCC model is one of the pioneer models in DEA and assumes variable returns to scale (VRS). In its input-oriented form it aims to minimize the inputs, given a fixed level of outputs.

The formulation of the empirical model is as follows. Let $\{UCITS_j\}$, $j \in \{1,\ldots,N\}$, be a set of N *DMUs*, that use the same n=2 inputs to achieve the same m=3 outputs.

Outputs for an $UCITS_j$ are average the daily return R_j, indicator of stochastic non-dominance SD_j and skewness coefficient $SKEW_j$. The inputs are *Expected Shortfall* ES_j and semi-variance SV_j. Therefore, a $UCITS_j$ is described by an output vector $\mathbf{X}_j = \left(R_j, SKEW_j, SD_j\right)^T$ and an input vector $\mathbf{Y}_j = \left(ES_j, SV_j\right)^T$

For each $UCITS_0 = UCITS_j$, $j \in \{1,\ldots,N\}$, the virtual output and virtual input is formed given the (initially) unknown nonnegative weights (v_r), r=1,2 and (u_i), i=1,2,3. These weights are determined by solving fractional programming problem (multiplier model) for each $UCITS_0$:

$$\begin{aligned} &\max_{v_1,v_2,u_1,u_2,u_3} \theta = \frac{u_1R_0 + u_2SKEW_0 + u_3SD_0}{v_1SV_0 + v_2ES_0}, \\ &s.t. \\ &\quad \frac{u_1R_j + u_2SKEW_j + u_3SD_j}{v_1SV_j + v_2ES_j} \le 1, \quad (j = 1,2,...,n) \\ &\quad v_1, v_2, u_1, u_2, u_3 \ge 0. \end{aligned} \tag{0.1}$$

An $UCITS_j$ which has the greatest ratio of virtual outputs to virtual inputs is considered the most efficient. However, given the constraints in (1.1), it is obvious that the efficiency ratio lies in the $[0,1]$ interval. Therefore, every *UCITS* that has an efficiency score 1 is considered relatively efficient, and all others are considered relatively inefficient. Using the Charnes-Cooper transformation [8], fractional programming model (1.1) can be linearized and written in its envelopment form [9]. The efficiency scores θ are determined by solving the linearized input-oriented BCC model with slack variables:

$$\min\left(\mathbf{0}^T\boldsymbol{\lambda}-\varepsilon\mathbf{e}^{\mathrm{T}}\mathbf{s}^{+}-\varepsilon\mathbf{e}^{\mathrm{T}}\mathbf{s}^{-}+\theta\right)$$

$$s.t.$$

$$\sum_{j=1}^{N}\mathbf{Y}_j\lambda_j-\mathbf{s}^{+}=\mathbf{Y}_0,$$

$$-\sum_{j=1}^{N}\mathbf{X}_j\lambda_j-\mathbf{s}^{-}+\mathbf{X}_0\theta=\mathbf{0}, \tag{0.2}$$

$$\sum_{j=1}^{N}\lambda_j=1,$$

$$\boldsymbol{\lambda},\mathbf{s}^{+},\mathbf{s}^{-}\geq\mathbf{0},$$

where $\boldsymbol{\lambda}$ is the Lagrangian variable, $\boldsymbol{s}^{+}$ and $\boldsymbol{s}^{-}$ are vectors of input and output slack variables and $\varepsilon>0$ is an infinitesimally small non-Archimedean element [25:23]. The values of slack variables indicate whether it is possible for a DMU to expand a particular output or reduce a particular input. A bundle $\left(\mathbf{X}_j,\mathbf{Y}_j\right)$ is Pareto efficient if all output and input slacks are equal to zero [29:34].

The analysed period is divided into *P* subperiods: $T_1,\ldots,T_p,\ldots,T_P$ such that

$$T=\bigcup_{p=1}^{P}T_p,\ T_p=\left\{t^{(p-1)}+1,t^{(p-1)}+2,\ldots,t^{(p)}\right\},\ p\in\left\{1,\ldots,P\right\},\ t^{(0)}=0.$$

The number of observations within a subperiod T_p is n_p. The model (0.2) is then solved for each $UCITS_0 \in \{UCITS_j\}, j \in \{1,\dots,N_p\}$, in each subperiod. The inequality $N_p > \max\{mn, 3(m+n)\}$ should hold for each subperiod $p \in \{1,\dots,P\}$, which is a recommendation (not a rule) for the stability of DEA [25:24]. Values of input and output variables for a $UCITS_j$ in a period T_p are calculated using the following formulas:

$$R_{T_p,j} = \frac{\sum_{t\in T_p} r_{tj}}{n_p},$$

$$SV_{T_p,j} = \frac{\sum_{t\in T_p} \left(R_{T_p,j} - r_{tj}\right)_+^2}{n_p},$$

$$SKEW_{T_p,j} = \frac{\sum_{t\in T_p} \left(r_{tj} - R_{T_p,j}\right)^3}{n_p \cdot s_{T_p,j}^3}, s_{T_p,j} = \sqrt{\frac{\sum_{t\in T_p} \left(r_{tj} - R_{T_p,j}\right)^2}{n_p}},$$

$$VaR_{T_p,j}^{\alpha} = \max\left\{r_{tj} : P(r_{tj} < R_{T_p,j}) = \alpha, t \in T_p\right\},$$

$$ES_{T_p,j} = \frac{\sum_{t\in T_p} \left(VaR_{T_p,j}^{\alpha} - r_{tj}\right)_+}{n_p},$$

$$SD_{T_p,j} = \max\left\{n : j \in ESD_{T_p}^{n}\right\},$$

$$j \in \{1,\dots,N_p\},$$

$$p \in \{1,2,3\}.$$

ES is calculated for *VaR* at a 95% confidence and semi-variance is calculated for the expected return. $ESD^n_{T_p}$ denotes the SD-efficient set of *n*-th degree in a period T_p, using the SD test of non-dominance by Davidson and Duclos [13] up to the third degree. The critical test value is used from the SMM distribution (Studentized Maximum Modulus, [30]) for α=5%, $\nu=\infty$ degrees of freedom and k=100 check-points ($M^{100}_{0.05,\infty} = 4.409$).

4. Results

The analysed period was divided into 3 subperiods: pre-crisis (*T*1: 1/1/2005 – 15/11/2007), crisis (*T*2:16/11/2007 – 9/3/2009) and post-crisis period (*T*3:10/3/2009 – 31/12/2015) according to the classification of the Croatian National Bank [16:17]. The number of observations within each subperiod is n_1=742, n_2=342, n_3=1778. All UCITS funds with at least 62% of valid data in the observed period were included in the analysis. The number of funds in subperiods *T*1, *T*2 and *T*3 is N_1=32, N_2=41 and N_3=53, respectively.

Correlation coefficients between inputs and outputs among themselves in each period should not be significant, indicating that there is no redundant input or output in the model. Table 1 suggests that there is a significant correlation between *Expected Shortfall* and semi-variance, which are both input variables. However, both of these indicators are included in the analysis since they carry relevant and different information.

	SV	*ES*	*R*	*SKEW*	*SD*
SV	1/1/1				
ES	0,7/0,94/0,84	1/1/1			
R	0,30/-0,83 /-0,09	0,58/-0,93 /-0,03	1/1/1		
SKEW	-0,16/-0,27 /-0,08	-0,18/-0,36 /-0,09	-0,07/0,39 /-0,02	1/1/1	
SD	-0,33/-0,23 /-0,11	-0,46/-0,31 /-0,17	-0,22/0,4 /0,06	-0,13/0,13 /0,14	1/1/1

Table 1: *The correlation coefficients of variables in each period (T1/ T2 / T3)*

Table 2 shows the first 10 and the last 10 UCITS funds according to their DEA efficiency scores for each period. The results suggest that UCITS funds with different investment strategies (MM - money market, E – equity, MX –balanced, B – bond) are efficient in the three analysed periods. Specifically, the efficient funds in the pre-crisis period are mostly stock and money market funds, there is a clear dominance of money market funds in the financial crisis period, whereas there is no clear distinction of an efficient type of UCITS funds in the post-crisis period. The least efficient funds during the crisis were equity funds, and these findings relate to the post-crisis period as well. This confirms the impact of the financial crisis on equity funds in Croatia.

Pre-crisis period		Crisis period		Post-crisis period	
UCITS	SCORE	UCITS	SCORE	UCITS	SCORE
PBZNOVF (MM)	1	VBICASH (MM)	1	CAPIONE (B)	1
HPBGLOB (M)	1	PBZDOLL (MM)	1	PBZNOVF (MM)	1
RAICAMM (MM)	1	PBZNOVF (MM)	1	ALLPORT (M)	1
HYHICSH (MM)	1	RAICAMM (MM)	1	RAIACTV (E)	1
NCCGDEV (E)	1	ILRBRIC (E)	1	ZBEUROP (MM)	1
ERSMONY (MM)	1	CAPIONE (B)	0,9999	ZBPLUSF (MM)	1
ILIAZTG (E)	1	ZBPLUSF (MM)	0,9999	ERSMONY (MM)	1
ILRBRIC (E)	1	ERSMONY (MM)	0,9495	PBZENOV (MM)	0,9999
PBZEQTH (E)	0,8698	OTPMMKT (MM)	0,7594	ZBBONDF (B)	0,9999
HYHICSV (B)	0,7671	HYHICSH (MM)	0,4176	RAICAMM (MM)	0,9998
...		...		...	
ERSADRE (E)	0,2718	HYHIGWT (E)	0	RAFCEUR (E)	0,0001
CAPIONE (B)	0,1657	NCCEMBD (B)	0	NCCEMBD (B)	0,0001
ZBTREND (E)	0,0825	NCCGDEV (E)	0	NCCGDEV (E)	0,0001
RAIACTV (E)	0,0741	ZBAKTIV (E)	0	NCCNEUR (E)	0,0001
PBZENOV (MM)	0,0711	ZBEURAC (E)	0	ERSADRE (E)	0,0001
ZBEUROP (MM)	0,0599	ZBTREND (E)	0	ILIJUGE (E)	0,0001

ZBEURAC (E)	0,0468	ERSADRE (E)	0	KDENERG (E)	0
PBZDOLL (MM)	0,0245	ILIAZTG (E)	0	ZBBRICP (E)	0
ZBBONDF (B)	0,0056	ILIJUGE (E)	0	ILIAZTG (E)	0
KDPRVIZ (E)	0,0023	OTPINDK (E)	0	ILRBRIC (E)	0

Table 2: *The top 10 and last 10 UCITS funds by DEA scores*

The DEA model evaluates efficiency scores by benchmarking inefficient against efficient fund(s). Using these efficient funds as benchmarks allowed us to isolate peer units and peer groups. Peer groups appear to be rather consistent with the investment strategy of UCITS funds, especially in the pre-crisis and crisis periods. In the post-crisis period, huge diversity can be recognized since equity funds are all benchmarked to different funds with different investment strategies. Also, a peer group of a benchmark fund gathers UCITS that significantly differ by investment strategy.

Pre-crisis	ERSMONY (MM)	ILIAZTG (E)	HYHICSH (MM)	RAICAMM (MM)
	ZBEUROP (MM)	ILIAZTG (E)	RAIBNDS (B)	ZBTREND (E)
	PBZENOV (MM)		PBZBOND (B)	ZBGLOBL (MX)
	PBZDOLL (MM)	ILRBRIC (E)	HYHICSV (B)	ZBEURAC (E)
	OTPMMKT (MM)	ILRBRIC (E)	HYHICSH (MM)	ZBBONDF (B)
	ERSMONY (MM)			RAICAMM (MM)
		PBZNOVF (MM)	NCCGDEV (E)	RAIACTV (E)
	HPBGLOB (MX)	PBZNOVF (MM)	RAFCEUR (E)	KDVICTO (E)
	PBZGLBH (MX)		NCCGDEV (E)	KDPRVIZ (E)
	HYHIBAL (MX)		ILIJUGE (E)	KDBALAN (MX)
	HPBGLOB (MX)		ERSADRE (E)	CAPIONE (B)

Crisis	PBZDOLL (MM)	ILRBRIC (E)	RAICAMM (MM)	VBICASH (MM)
	PBZDOLL (MM)	ZBTREND (E)	ZBAKTIV (E)	ZBGLOBL (MX)
		ZBEURAC (E)	RAICAMM (MM)	ZBEUROP (MM)
	ZBPLUSF (MM)	RAIACTV (E)	NCCGDEV (E)	ZBBONDF (B)
	ZBPLUSF (MM)	RAFCEUR (E)	RAICAMM (MM)	VBICASH (MM)
		PLATGOP (E)	ZBAKTIV (E)	RAIBNDS (B)
	PBZNOVF (MM)	PBZEQTH (E)	RAICAMM (MM)	PLBLCHP (E)
	PBZNOVF (MM)	NCCEMBD (B)		PBZISTK (E)
	PBZGLBH (MX)	KDVICTO (E)		PBZENOV (MM)
	OTPMMKT (MM)	KDPRVIZ (E)		PBZBOND (B)
	HYHICSH (MM)	ILRBRIC (E)		OTPINDK (E)
	ERSMONY (MM)	ILIAZTG (E)		NCCFRNT (E)
		HYHICSV (B)		KDNOVEU (E)
	CAPIONE (B)	ERSADRE (E)		KDBALAN (MX)
	CAPIONE (B)			ILIJUGE (E)
				HYHIGWT (E)
				HYHIBAL (MX)
				HPBGLOB (M)
Post-crisis	ALLPORT (MX)	ERSMONY (MM)	PBZENOV (MM)	RAICAMM (MM)
	ZBGLOBL (MX)	ZBBRICP (E)	PBZENOV (MM)	VBICASH (MM)
	ZBAKTIV (E)	VBSMART (E)		RAICAMM (MM)
	PBZISTK (E)	RAFCEUR (E)	RAIACTV (E)	RAIBNDS (B)
	OTPINDK (E)	PBZBOND (B)	RAIACTV (E)	KDPRVIZ (E)
	NCCFRNT (E)	OTPMMKT (MM)		KDNOVEU (E)
	NCCALGO (E)	NCCNEUR (E)	ZBBONDF (B)	KDBALAN (MX)
	HYHIGWT (E)	NCCGDEV (E)	ZBBONDF (B)	HYHICSV (B)

	HYHIBAL (MX)	NCCEMBD (B)		
	ALLPORT (MX)	KDVICTO (E)	PBZNOVF (MM)	
		KDENERG (E)	PBZNOVF (MM)	
	CAPIONE (B)	ILRBRIC (E)	PBZDOLL (MM)	
	ZBTREND (E)	ILIJUGE (E)		
	PLBLCHP (E)	ILIAZTG (E)		
	PLATGOP (E)	HPBGLOB (MX)		
	PBZGLBH (MX)	ERSMONY (MM)		
	PBZEQTH (E)	ERSADRE (E)		
	CAPIONE (B)	EEMONYA (MM)		
		CROBX10 (E)		
		ALLCASH (MM)		
		AGRAMTR (MX)		

Table 2: *The peer groups of efficient benchmark UCITS funds*

Finally, for the first 15 funds, the ranking obtained using DEA was compared to the Information ratio[‡] (IR), and the rankings are significantly different, as shown in Table 4. This indicates that using only IR as an indicator of relative performance of UCITS funds is rather misleading for both investors and regulators who have the same set of preferences.

Pre-crisis			Crisis			Post-crisis		
UCITS	DEA	IR	UCITS	DEA	IR	UCITS	DEA	IR
PBZNOVF	1	27	VBICASH	1	41	CAPIONE	1	38
HPBGLOB	1	20	PBZDOLL	1	32	PBZNOVF	1	45
RAICAMM	1	31	PBZNOVF	1	40	ALLPORT	1	40
HYHICSH	1	30	RAICAMM	1	35	RAIACTV	1	32
NCCGDEV	1	13	ILRBRIC	1	31	ZBEUROP	1	48
ERSMONY	1	32	CAPIONE	1	15	ZBPLUSF	1	50
ILIAZTG	1	12	ZBPLUSF	1	38	ERSMONY	1	51
ILRBRIC	1	1	ERSMONY	8	37	PBZENOV	1	44

[‡] Calculations based on the EONIA daily rate for money market funds, CROBEX and CROBIS for equity and bond funds and their weighted (0,24-0,39-0,37) rate for balanced funds.

PBZEQTH	9	9	OTPMMKT	9	36	ZBBONDF	1	39
HYHICSV	10	25	HYHICSH	10	39	RAICAMM	10	49
HYHIBAL	11	14	ZBEUROP	11	33	ZBEURAC	10	31
PBZGLBH	12	18	PBZENOV	12	34	EEMONYA	12	47
ILIJUGE	13	11	ZBBONDF	13	27	HYHICSH	12	52
HYHIGWT	14	8	HYHICSV	14	21	AUCTCSH	12	53
RAFCEUR	15	7	PBZBOND	15	24	HYHIGWT	12	28

Table 3: *The peer groups of efficient benchmark UCITS funds*

5. Conclusions

The results suggest that DEA is useful for performance testing of UCITS funds and it complements traditional measures. The paper contributes to the development of the adjusted DPEI index. This paper's contribution is also evident in analysing the Croatian UCITS fund market, a market characterised as less developed. The results of the analysis in this paper confirm the impact of the financial crisis on UCITS funds in Croatia. An analysis indicated that the efficiency of UCITS funds changed across the three analysed periods. The efficient funds in pre-crisis period are primarily stock and money market funds, those dominating in the period of financial crisis are money market funds - as expected, whereas in the post-crisis period no type of UCITS funds shows a clear dominance. Peer groups of corresponding efficient funds are rather coherent regarding their investment strategy, especially in case of pre-crisis and crisis period. In the post-crisis period, huge diversity is seen and a peer group of an individual benchmark portfolio gathers UCITS that are very different by investment strategy. The rankings of funds obtained by DEA methodology differ to the rankings obtained by Information ratio. Overall, the conclusion is that money market funds seem to be the most efficient type of UCITS funds in Croatia, as supported by both ranking analysis and obtained benchmark portfolios.

Further research should test different inputs and outputs and compare the results with traditional absolute and relative risk-adjusted performance measures of mutual funds. Furthermore, window analysis should also be conducted, as well as analysing changes in relative efficiency for each fund across different periods. Valuable research outcome would be to identify a connection between results of DEA and the investment strategy of efficient funds and to detect a more detail investment approach and similar characteristics of efficient funds.

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