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Investors' Decision-making Under Risk: Evidence from the Croatian Stock Market

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ABSTRACT

Purpose:
This article deals with the retail investors' decision-making under risk, firstly addressing several theories of decision-making under risk. Following this theoretical framework, an analysis on investment strategies on the Croatian capital market has been conducted.

Design/methodology/approach:
In this paper a non-parametric Data Envelopment Analysis (DEA) methodology is used to estimate input-oriented efficiency (minimization of risk i.e. stock return volatility, standard deviation) in retrospect to monthly stock returns of 15 selected stocks (due to a liquidity criteria) and five stock indices on the Croatian stock market in the period from 2016 until 2021.

Findings:
Results show that just but a few stocks provide high efficiency levels on the Croatian stock exchange, while the general CROBEX stock index proves to be a viable investment option for retail investors whose financial knowledge, expertise and time are limited.

Research limitations/implications:
This study was conducted on a limited sample of 15 most liquid stocks and five stock indices on the Croatian stock market in the period from 2016 until 2021. Due to the limited number of liquid stocks through time, the shallowness and illiquidity of the Croatian stock market provides a major limitation of this study. Furthermore, the limited sample attained dictated the use of nonparametric static DEA methodology that is suboptimal. For future studies, it is recommended to internationally expand the sample and use dynamic nonparametric and parametric techniques in stock efficiency estimation.

Originality/value:
The main aim of the study was to provide a theoretical overview on the theories of decision-making under risk. These theories provide insight that investors (retail but institutional nonetheless) are more loss avoidant than return seeking (risk aversion) which in the end affects their optimal investment strategy. In addition, this study used DEA methodology in efficiency estimation of 15 stocks on the Zagreb Stock Exchange (ZSE). The results from this study suggest that for untrained and inexperienced retail investor the investment in the general stock index could be a viable investment strategy. This study builds upon several studies on investment strategies on the Croatian stock market by providing more insight on stock and stock indices returns and efficiency several years previously and during the COVID-19 pandemic. Future studies dealing with similar topics should expand to a multinational sample that would solve the two main limitations of this study. Therefore, by expanding the sample to neighbouring countries, and increasing the number of liquid stocks observed and the possibility of using dynamic nonparametric and stochastic models in efficiency estimation of stocks to determine adequate investment strategies.

1. Introduction

The field of study that focuses on decision-making under risk has been in development now for seventy years. However, the notion of uncertainty and risk is old as humanity itself since there was, and always will be variability of outcomes to our decisions. Whether we are aware of the probabilities of those outcomes (risk), or the probability distribution is unknown (uncertainty) there are no riskless decisions. Certainly, there is variability in the size and occurrence of risk tied to a decision. Closest to true riskless decisions are decisions with risk low enough in combination with enormous benefits (outcomes) that in retrospect to their risk can be deemed negligible and subsequently could be discarded from the decision-making process. A true riskless decision is only achieved in a hypothetical situation where there is only one outcome that has no variability and therefore its certainty of occurrence is unquestionable (probability of occurrence of the outcome is 1 or 100%). A basic definition of risk would be the variance of the probability distribution of possible gains and losses attributed to a specific decision.

This paper deals with relevant theories of decision-making under risk, taking a special interest on brokers, retail, and institutional investors' behaviour on the of Croatian stock exchange. The main goal of this study is to present current decision-making theories under risk. Furthermore, this paper aims to provide empirical evidence on investment strategies of retail investors and asses their validity on the Croatian stock market firstly defining efficient stocks on the ZSE (Zagreb Stock Exchange, i.e. the equivalent of the Croatian stock market). The estimation of efficient stocks is achieved using DEA methodology using constant and variable returns to scale. In the following section, a brief theoretical background on decision-making under risk from economics, psychology, and biology is presented. The same section also provides a brief literature review on current studies on investment strategies, efficient portfolios and stock estimation, and investors' behaviour on the stock market. The methodology used in this paper is presented in the third section, with a brief statistical overview of the data. In the subsequent section, results of the optimization model are discussed. The final, fifth section highlights the main conclusions of this empirical study and provides recommendations for future research.

2. Review of Literature

2.1 Theoretical Review

In economics, the Theory of Utility of Wealth remains a dominating theoretical framework for decision-making under risk. This theory describes a s-function of utility of wealth, concave in the first part, and it is convex in the second part, explaining the risk averse and risk seeking behaviour od decision maker first conceptualized by Friedman & Savage (1948). The theory was further expanded by (Markowitz, 1952b). Describing a rational individual means that more wealth is always preferred, (more wealth is always better), however subject to a diminishing marginal utility with any additional monetary unit. Therefore, Friedman & Savage (1948) and Markowitz (1952b) describe investors' behaviour decision-making under risk using the expected utility theory framework, describing individuals risk averse (concave), risk seeking (convex) and risk neutral regarding their willingness to tolerate potential losses.

Nonetheless, in the past seventy years there have been many breakthroughs in studies conducted on understanding of decision-making under risk. Today, decision-making is an interdisciplinary topic, it is extensively researched in the fields of psychology, economics, but also in biology. An integrated view to the most influential theories of decision-making such as expected utility theory, prospect theory, heuristic approaches and risk-sensitivity theory is provided by Mishra (2014). Integrating these widely broad and inconsistent perspectives to develop a synthesis of all these theories, creating a general theory of decision-making under risk is challenging.

However, greater understanding of human behaviour under risk and its decision-making process would provide significant improvement in predicating human behaviour in general. The benefits of this integration are not just present in advancing the fields of psychology and biology, but in economics in terms of investors and decision-makers (consumers) behaviour. Better understanding of investors' actions on the financial markets could be proven useful in developing more efficient investment strategies, and in the long run affect improve the stability of the financial system. This process of integration has already started with combining elements from psychology and economics, creating a new field of behavioural economics, or behavioural finance that attempts to relax the limitations of the rationality postulate of neoclassical economics.

The core of Expected Utility Theory was already briefly addressed in the previous paragraph, it is necessary to briefly elaborate on other decision-making under risk theories. Firstly, the prospect theory developed by Kahneman & Tversky (1979). Prospect theory started as a critique to the expected utility theory descriptive power of decision-making under risk. A good overview of prospect theory is provided by Barberis (2013) who addresses its use in finance explaining the disposition effect and the momentum effect. Empirical research on the disposition effect, and other individual investors fallacies are provided by (Barber et al., 2009; Barber & Odean, 2000; Odean, 1998).

Further development in explaining behaviour and decision-making under risk are heuristic approaches ("rules of thumb" an efficiency algorithm in decision-making) provided by the work of Slovic and his colleagues (for an outline of heuristic approaches see (Finucane et al., 2000; Slovic, 1972, 1993; Slovic et al., 1972, 1985, 2004, 2007). One important socioeconomic trait of investors is trust, in its counterparties, the market, and economic theory. Chiles & McMackin (1996) state that within the paradigm of transaction cost economics managers have variable risk preferences, as well as the importance of trust in transactions. Trust is an economizing agent, reducing transaction

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costs, eliminating and reducing unnecessary bureaucracy and making business transactions more efficient. Authors' define trust as the person's increase in vulnerability to the risk of opportunistic behaviour to the person's transaction partner, while the other person's (transaction partner) behaviour is not under its control. Furthermore, the situation dictates that the costs of violating trust are (much) greater than the benefits of upholding the trust. The final decision-making theory comes from the field of biology. Risk-sensitivity theory as described by Mishra (2014) is a normative theory that explains decision-making on the premise (assumption) that organisms ultimately behave to enhance their reproductive success or fitness see (Hintze et al., 2015; Kacelnik & Bateson, 1997; Satchell et al., 2018; Weber et al., 2004).

Risk-sensitivity theory explains that for decision-makers is not necessary to maximize desirable outcomes (energy budget requirements, in modern terms level of income) but rather the goal is to optimize the fulfilment of one's needs. In other words, the decision-making strategy is to avoid outcomes that fail to meet these needs, and to focus on outcomes that are "good enough" to meet the basic needs at any given time (Maslow's pyramid (hierarchy) of needs).

In this chapter prominent theories of decision-making under risk where presented. The following chapter deals with a brief literature review of current empirical studies on investors' decision-making behaviour.

2.2 Previous studies

Investment decisions are a trade-off between immediate consumption and deferred consumption. In other words, investments are decisions on current gratification (utility maximization) and delayed gratification with risk (decreased utility in the present with the goal of higher satisfaction in the future). This definition is in close relation to the famous Marshmallow test, however in the test there is no variation in the outcomes, as they are guaranteed. Therefore, there is no risk in such situations, a clear departure from the real world of stock investments. On the other hand, investments are subject to volatility i.e. variation of outcomes that can differ in retrospect to the expected outcome that is the basic definition of risk in modern finance. Even though economic theory at its core relies on the rationality postulate, decisions made by individual investors are still subjected to emotion, biases, intuition, and limitations of their statistical knowledge.

Furthermore, institutional investors are just complex organizations consisting of professional investors that in the end are still human. Consequently, they subject to the same behavioural challenges, fallacies (although not to the same extent) as individual investors (Slovic, 1972, p. 780) states that most of the time people bypass formal statistical procedures when making judgements, becoming "intuitive statisticians". Investors (individual and professional) and brokers' intuition still presents the majority of their decision-making process. Subjective predictions are based on the state of mind, feelings and attitudes, not necessarily knowledge, and they are not entirely the product of well-defined reasoning. Investors' decision-making is not as rational as thought to be, and very few investors, or investment firms are able to beat the market in the long run. Furthermore, there seems to be empirical evidence (see Slovic, 1972, p. 787) that longer work experience of a broker in the valuation and investment business made his insight into his weighting policy (decision-making process) less accurate – less clear. Even with formal training in statistic, people more than often rely on their intuition to make the final decision. Slovic (1972, p. 796) argues that decision made in groups are on average riskier than decisions made by individual investors, and it seems that individual risk-taking levels increased following group discussion. This behaviour could be explained by herd behaviour where each individual investor feels less personal blame in the case of losses. In other words, following the group, individual investor's responsibility is diffused to the group, making the investor less afraid, and more prone to riskier investments – exhibiting risk-seeking behaviour. Slovic et al. (1972) suggested that the use of mathematical models such as the analysis of variance (ANOVA) or multiple regression (even if not entirely optimal) could be useful in improving investors' decision-making. Authors argue that since human (investor's) decision-making tends to become erratic, affecting their accuracy due to errors in judgment, the use of mathematical models will reduce these errors, improving investor's judgment and enhancing their success on the stock market. Therefore, it is possible to deduce that individual investors are prone to irrational investment decisions, see (Gill et al., 2018; Hilton, 2001; Kafayat, 2014; Odean, 1998b; Sarwar & Afaf, 2016; Syed & Bansal, 2018).

On the other hand, Forlani & Mullins (2000) study the perceived risks and choices in entrepreneurs' new venture decisions. By the nature of their work, entrepreneurs do not see themselves as risk takers, but as opportunity takers that others do not see. In authors' opinion, there is a distinction between entrepreneurs' perceptions of risk and decisions involving risk arguing that they are separate cognitive processes. The conclusions raised are that entrepreneurs are more prone to choose ventures with higher hazard (grater loss and gains) with low probability. Finally, there is evidence that entrepreneurs exhibit risk propensity while choosing new ventures, while risk perception remains present and unchanged. Behavioural finance as a new field has a difficult task of identifying and defining the idiosyncrasies of investors' decision-making. Decision-maker's preferences are complex, open to change, and often formed or influenced during the decision process itself. Langevoort (1996) presents the dynamic relationship between stockbrokers and their sophisticated customers – investors. Stockbrokers offer their professional expertise to buy and sell financial products on behalf of their clients to maximize their returns – profits since most of the time their compensation for brokerage services is based on the volume and intensity of the trading orders.

Additionally, the sophisticated costumer (investor) uses brokers' services to save on time, transaction costs, and to gain, collect additional information, as well as, psychologically transferring some responsibility of investments made. Therefore, brokers are often tempted to mischaracterize an investment's level of risk, while investors may behave excessively risk seeking when offered an investment opportunity by the broker. The relationship between brokers and investors is fruitful when the investments generate at least positive or expected returns. Great losses will incentivize investors to blame brokers for the misfortune, since they have made the investment based on their advice. As in all human relationships, trust takes a central place between the brokers and investors professional relationship. According to the author, brokers tend to be motivated not only by their training, but also by their goal of maximizing commission income to gain, build and cultivate investors trust. Investors on the other hand, are influenced to inherently trust the broker, and their trust level will rise if brokers' advice and recommendations prove to be true and profitable (importance of trust on professional relationships have been studied by Chiles & McMackin, 1996; Slovic, 1993).

However, when investments generate large losses, investors will blame their brokers for inaccurately disclosing information on the risk of investment or for giving bad advice. Brokers will defend themselves by indicating that the losses are a product of investor's greed that incentivized them to invest in investments with greater risk that promised greater returns, and now are not able to take on the responsibility for the occurred losses. Finally, it is necessary to impose caution when investing and following investment advice from brokers, moderation and restraint are advised to investors, since brokers deal with the sale of hope but also risk that is out of anybody's control.

There are several empirical studies conducted on the Croatian stock market i.e. Zagreb stock exchange (ZSE) that address investment strategies of Croatian investors. A study from Altaras Penda (2017) shows that there is no correlation between publicly listed Croatian companies' financial performance (income) and stock price, contradicting decades of economic and financial theory, indicating investors' irrational behaviour on the ZSE. The only certainty is market volatility (change of prices), market socks, risk and uncertainty. (Erjavec & Cota, 2007) investigate the influence of international financial markets on the short-term volatility of ZSE. Empirical results show that American stock exchange indices movements influence – affect the direction of change of the CROBEX index. The effect of changes in stock market index composition on stock returns on the ZSE is empirically tested by Škrinjarić (2019). Main findings show that investors in short term devalue stocks (producing negative returns) upon their exclusion from the market index (CROBEX). Furthermore, an investigation on investment strategy on the ZSE by implementing a dynamic DEA methodology is provided by Škrinjarić (2014). Results suggest that using DEA methodology can be useful in detecting – identifying efficient stocks (optimal stocks providing the best return-risk ratio i.e. the maximum return and the lowest risk). Furthermore, the dynamics between risk and performance of ZSE stock indices is studied by (Škrinjarić , 2015). Empirical results suggest that using MGARCH dynamic models can be a useful investing strategy on the ZSE. Portfolios based on the implemented methodology outperformed the market, as well as, average portfolios, in terms of return and risk. The Croatian stock market is problematic because of its shallowness and low liquidity. Investors have just but a couple dozen stocks to choose from that are considered liquid enough, traded regularly (monthly) to be deemed a viable investment. These limitations put to the test the traditional market theories from economics (for reference, and empirical evidence on the applicability of the SML model on the Croatian capital market see (Benazić & Uč kar, 2018; Uč kar & Nikolić , 2008).

3. Methodology and data

In this paper, following the methodology used by (Škrinjarić , 2014) in using the Data Envelopment Analysis (DEA) as a method of estimating efficient stocks and devising potential investment strategies that would predominantly outperform the market. However, in retrospect to Škrinjarić (2014) where monthly data of 26 stocks from ZSE in the period from April 2009 until June 2012. The period used in this paper is from January 2016 until December 2021 using weekly stock returns. Weekly stock returns are calculated using ZSE data at the end of the day (closing price) for every Friday in the observed period. In the case that there were no transactions of a stock on a Friday, the closing price of the previous trading day was subsequently taken into account.

The use of weekly data is actually one of the recommendations of the before mentioned paper, since it could reflect intra-month oscillation. Selected stock indices (due to liquidity constraints and continuity of the stock index) were examined, one general (CROBEX), and four sectoral: CROBEXindu (industry), CROBEXkons (construction), CROBEXnutr (nutrition), CROBEXturi (tourism). Furthermore, only 15 stocks listed on the ZSE were selected for the same liquidity reasons in the period from January 2016 until December 2021. Most of these stocks are also part of the examined sock indices. This limited sample of just 15 stocks gives insight into the characteristics of the Croatian capital market. The market is shallow and illiquid, in the sense that there are not many investment options available to institutional, but also retail investors (shallowness of the market). However, institutional investors have the ability to invest internationally, being able to access international capital markets and possessing the time and expertise in international investing. Liquidity concerns are also a limiting factor, given the small number of choices on the ZSE. Institutional as well as the retail investors must define their liquidity criteria, and subsequently even further limit their investment options on the Croatian capital markets. The observed stocks are AD Plastik (ADPL), Adris grupa. (ADRS), Arena Hospitality Group (ARNT), Atlantic grupa (ATGR), Atlanska plovidba (ATPL), Dalekovod (DLKV), Ericsson Nikola Tesla (ERNT), Hrvatski Telekom (HT), Konč ar (KOEI), Kraš (KRAS), Maistra (MAIS), Podravka (PODR), Valamar Riviera (RIVP), Brodogradilište Viktor Lenac (VLEN), and Zagrebač ka banka (ZABA). Monthly returns R_{ik} for i-th stock in the k-th, i ∈ {1,2,…,20}, k ∈ {1,2,…,72} month are attained as the average of weekly returns that are calculated using the following formula, without taking into account dividends:

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$$R_{ik} = \frac{\sum_{j=1}^{n_k} r_j^{ik}}{n_k} \quad (1)$$

$$r_j^{ik} = ln\frac{P_j^{ik}}{P_{j-1}^{ik}}, j \in \{1, \ldots, n_k\} \quad (2)$$

Where r_j^{ik} is j-th weekly return on Friday j that is calculated as a natural logarithm of closing price P_j^{ik}on Friday j of i-th stock (index) in the k-th month divided by i-th stock (index) in the k-th month price from the week (on Friday j-1) before P_{j-1}^{ik}. Finally, n_k is the number of weeks in the k-th month. Monthly returns are plotted in the Graph 1 in the Appendix that provides some insights in the movement of returns in the observed period.

Firstly, investors (being institutional or retail) cannot make an investment decision based just on the return alone. In general, stocks (and indices) have similar returns throughout the observed period. Therefore, additional testing is needed based on variance of returns (standard deviation) or using fundamental analysis data (financial indicators) in estimating the best (most efficient) investment options in this sample. Averaged monthly stock (indices) returns in general move from 10% to -10% but averaging to 0,15% in the observed period. Only a few stocks generate higher average monthly returns, their maximal values are over the arbitrary 10% threshold, ADRS (20.63% in February 2020), ATPL (12.36% in October 2016), DLKV (89,89% in July 2021 as a consequence of merging 100 shares in one the same month), KRAS (24,9% in September 2019), VLEN (11,67% in March 2016). The Nutrition index (CROBEXnutr) achieves a maximum return of 10,86% (September 2019). However, returns are just one motive for investors' decision-making, as the common postulate in finance states, higher returns dictate higher risk levels and vice versa. Modern portfolio theory (MPT) is an optimization program in choosing stocks (portfolios) with an optimal ratio of risk and return based on the investor's risk preference (Markowitz, 1952a). The basis for risk in MPT is return dispersion around the mean (mean variance, or standard deviation). Therefore, when analyzing stock returns it is necessary to study standard deviation as a measure of volatility, or risk. For this reason, makes sense to implement a DEA methodology on stocks in estimating their "efficiency" since it is a linear programming model of optimization (seeking the best returns in respect to the lowest risk – standard deviation). Standard deviation is calculated as:

$$\sigma_{ik} = \sqrt{\frac{\sum_{j=1}^{n_k}(r_j^{ik} - R_{ik})^2}{n_k}} \quad (3)$$

Summary statistics of the calculated variables are presented in the following Table 1.

Table 1 Summary statistics of weekly returns for the observed stock indices and individual stocks in the period from January 2016 until December 2021

Stock (Index)	Minimum	Maximum	Average	Standard deviation
CROBEX	-6,14%	1,78%	0,08%	1,07%
CROBEXindu	-7,39%	4,59%	0,06%	1,60%
CROBEXKons	-10,35%	6,93%	0,03%	2,82%
CROBEXnutr	-7,31%	10,86%	0,03%	2,00%
CROBEXturi	-6,84%	3,24%	0,13%	1,28%
ADPL	-12,76%	5,13%	0,19%	1,99%
ADRS	-17,95%	20,63%	0,12%	3,47%
ARNT	-12,61%	4,30%	0,00%	2,01%
ATGR	-4,55%	3,08%	0,24%	1,16%
ATPL	-13,45%	12,36%	0,42%	3,97%
DLKV	-36,80%	89,89%	0,33%	11,93%
ERNT	-3,21%	3,32%	0,19%	1,13%
HT	-1,86%	2,34%	0,09%	0,84%
KOEI	-5,02%	4,61%	0,11%	1,39%
KRAS	-7,62%	24,97%	0,18%	3,39%
MAIS	-7,60%	4,00%	0,12%	1,42%
PODR	-4,58%	5,24%	0,23%	1,34%
RIVP	-9,86%	4,01%	0,10%	1,86%
VLEN	-6,63%	11,67%	0,20%	3,58%
ZABA	-5,03%	3,14%	0,18%	1,37%

Source: Author's construct based on Zagreb Stock Exchange trading data ZSE (www.zse .hr) in the period from January 2016 until December 2021.

As mentioned before, several studies recently implemented DEA methodology on the Croatian stock market see (Gardijan & Kojić , 2012; Gardijan & Škrinjarić , 2015; Škrinjarić , 2014, 2015). With the goal of estimating individual efficient stocks, DEA (Data Envelopment Analysis) methodology is used. DEA is a linear programming method that benchmarks the DMU's (decision-making units) regarding their distance to the efficiency frontier. However, stocks are more of assessment units than decision-making units (DMU). The methodology was first established by Charnes et al. (1978) for a model that assumes constant returns to scale (CRS) often called "CCR model". Further improvements were provided by Banker et al. (1984) by incorporating additional constraints allowing for variable returns to scale (VRS) often called BCC model. Both models can be input (minimization) or output (maximization) oriented. Following these seminal papers, the methodology was additionally developed in several directions (addressing the effect of environmental variables, undesirable outcomes, incorporating stochastic elements, dynamic models, network models, etc.). Only a brief overview of the general model is provided here.

The DEA model is calculated as the ratio of weighted outputs to weighted inputs for each DMU as shown in (4) to (7). It is necessary to obtain values for the input "weights" (v_i) where i = 1,..., m and the output "weights" (u_r) where r = 1,..., s.

$$\max_{u,v} \theta\,(u, v) = \frac{u_1 y_{1j} + u_2 y_{2j} + \cdots + u_s y_{sj}}{v_1 x_{1j} + v_2 x_{2j} + \cdots + v_m x_{mj}} = \frac{\sum_{r=1}^{s} u_{r0}}{\sum_{i=1}^{m} v_i x_{i0}} \quad (4)$$

subject to

$$\frac{u_1 y_{1j} + \cdots + u_s y_{sj}}{v_1 x_{1j} + \cdots + v_m x_{mj}} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \text{ where j} = 1, \ldots, \text{n} \quad (5)$$

$$u_r \geq 0, \text{r} = 1, \ldots, \text{s} \quad (6)$$

$$v_i \geq 0, \text{i} = 1, \ldots, \text{m} \quad (7)$$

Since the fractional programming model from (4) to (7) has an infinite number of solutions (the optimal solutions u*, v* allow that every positive scalar c, (cu*, cv*) is also optimal). In order to simplify and solve the fractional programming model it is necessary to define the weighted sum of input variables equal to one (8). Using this transformation in it is possible to select a representative solution (u, v) constructing the linear programming model in (9) to (13) that is also known as the CCR model.

$$\sum_{i=1}^{m} v_i x_{i0} = 1 \quad (8)$$

$$\max_{u,v} z_0 = \mu_1 y_{1o} + \cdots + \mu_s y_{so} = \sum_{r=1}^{s} \mu_r y_{r0} \quad (9)$$

subject to

$$\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, j = 1, \ldots, n \quad (10)$$

$$\sum_{i=1}^{m} v_i x_{i0} = 1 \quad (11)$$

$$\mu_r \geq 0, \text{r} = 1, \ldots, \text{s} \quad (12)$$

$$v_i \geq 0, \text{i} = 1, \ldots, \text{m} \quad (13)$$

The dual of the CCR that assumes CRS (9) to (13) for each DMU can be written as:

$$\min_{\lambda} z_0 = \Theta_0 \quad (14)$$

subject to

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0}, r = 1, \ldots, s \quad (15)$$

$$\Theta_0 x_{i0} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0, i = 1, \ldots, m \quad (16)$$

$$\lambda_j \geq 0, \text{j} = 1, \ldots, \text{n} \quad (17)$$

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Where θ_0 is a scalar and its value denotes the efficiency score for the i-th DMU in our case stock, and λ_j is a Nx1vector of constants. Adding a convexity condition for λ_j (by setting the sum of components of the vector λ_j to one) the model now allows variable returns to scale (VRS) and it's the input-oriented BCC model (18) to (22):

$$\min_{\lambda} z_0 = \Theta_0 \quad (18)$$

subject to

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0}, r = 1, \ldots, s \quad (19)$$

$$\Theta_0 x_{i0} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0, i = 1, \ldots, m \quad (20)$$

$$\sum_{j=1}^{n} \lambda_j = 1 \quad (21)$$

$$\lambda_j \geq 0, \mathrm{j} = 1, \ldots, \mathrm{n} \quad (22)$$

Monthly average returns R_{ik} represents the output variable for every i-th stock in every k-th month, and standard deviation σ_{ik} represents the input variable for every i-th stock in every k-th month. Following the procedure proposed in da Costa Jr et al. (2008) of standardization, re-scaling, and normalization was implemented since standard DEA models do not accept negative values. Since DEA is a non-stochastic technique, it does not implement a random error term in efficiency estimation, and it is vulnerable to noise and computational mistakes, producing less accurate results. This procedure solves another problem since it makes the numeric instances more balanced and reduces the risk of imprecision of computation.

$$Z_{ij} = \frac{(X_{ij} - \overline{X_J})}{\hat{\sigma}_j} \quad (23)$$

The variables are standardized using the formula in (23) where the standardized result (Z_{ij}) for indicator j of i-th stock is calculated as the difference between the value of the indicator in i-th stock (X_{ij}) and the average of the indicator for all stocks ($\overline{X_j}$) divided by the standard deviation of the indicator j for all the stocks in the sample ($\hat{\sigma}_j$). Following the standardization, the data is re-scaled using the formula in (24):

$$RZ_{ij} = Abs(min\, Z_j) + Z_i \quad (24)$$

Where RZ_{ij} is the re-scaling for each j attribute, and the results are normalized by dividing all the attributes by the respective maximum as shown in (25).

$$MRZ_{ij} = \frac{RZ_{ij}}{Max\, RZ_{ij}} \quad (25)$$

The number of variables is further expanded to include several financial indicators following (Gardijan & Škrinjarić , 2015) such as debt ratio (DR as an input variable), current liquidity ratio (CL), return on equity (ROE) and stock turnover (T) as output variables since greater values of these indicators are desirable to investors. However, since these financial indicators are usually calculated on an annual basis, calculated weekly return and volatility data is averaged to annual values. Summary statistics incorporating financial indicators is presented in Table 2, while average correlation of variables for the whole period are given in the Table 3. Financial indicators included in the model were standardized, rescaled and normalized using formulas from (23) to (25).

Table 2 Variables summary statistics for the observed period

	Standard deviation	***Debt ratio***	***Return***	***ROE***	***Current liquidity ratio***	***Turnover (HRK)***
Average	4,49%	52,47%	0,15%	32,46%	1,73568	439.991
St. Dev.	7,54%	18,88%	0,70%	75,96%	1,348746	457.609
Maximum	70,59%	104,05%	4,88%	308,61%	10,36755	2.324.131
Minimum	0,96%	15,46%	-1,77%	-261,76%	0,04868	9.451

Source: Author's construct based on Zagreb Stock Exchange trading data ZSE (www.zse.hr), and financial statements data in the period from January 2016 until December 2021.

From Table 2 it is visible that the average yearly return is just 0, 15%, maximum is just 4,88% and minimum of -1,77% for the observed period. Furthermore, the strongest correlation is between return and its volatility of 0,52 and debt ratio (0,22) while almost no correlation was found between other observed variables as presented in the Table 3 (Correlation matrix).

Table 3 Correlation matrix of the used variables for the whole period from 2016 until 2021

Variable	*Standard deviation*	*Debt ratio*	*Return*	*ROE*	*Current liquidity ratio*	*Turnover*
Standard deviation	1	0,22	0,52	-0,12	-0,11	0,11
Debt ratio	0,22	1	-0,04	-0,05	-0,32	-0,06
Return	0,52	-0,04	1	0,07	-0,04	0,04
ROE	-0,12	-0,05	0,07	1	-0,02	-0,37
Current liquidity ratio	-0,11	-0,32	-0,04	-0,02	1	-0,11
Turnover	-0,11	-0,37	0,04	-0,06	0,11	1

Source: Author's construct based on Zagreb Stock Exchange trading data ZSE (www.zse.hr), and financial statements data in the period from January 2016 until December 2021.

Statistics in Tables 1-3 as well as Graph 1 represent the state of Croatian stock market. Even before the worst month of the observed period (March 2020 due COVID-19 disease lockdown) returns on the ZSE were small and as mentioned before, the market suffers from its shallowness and decreased liquidity. From the discussion in previous sections on the definition of risk and investors' behavior, and past empirical evidence, it is reasonable to assume investors are usually more risk and loss averse than return maximizing. Therefore, investors are more flexible on the return side (profit maximization), then on the loss side (negative returns, loss minimization). This reasoning arises from expected utility theory mentioned before (decreasing marginal utility of wealth – loss hurts more than gains make us happy). Following that, it is reasonable to assume that investors are more interested in minimizing risk (in our case standard deviation and debt ratio) at a given level of return than, maximizing them.

4. Results

Using data presented in the previous section, a static input-oriented DEA methodology was implemented using constant (CCR model) and variable returns to scale (BCC model). The efficiency results are presented in the following Tables 4 and 5. Efficiency results in Table 4 for the CCR model that assumes constant returns to scale show that only one stock (HT) is deemed efficient throughout the observed period. In this case, an efficient stock is providing the smallest risk in retrospect to the return attained. The second-best overall score is of the general CROBEX index which makes sense since it incorporates up to 30 most liquid stocks on the ZSE. This means that investing in the general stock index CROBEX is a valuable investment option in minimizing risk for retail investors, whose financial knowledge, expertise, and time is limited. Finally, there is a clear drop in efficiency in 2020 due to the COVID-19 pandemic. Otherwise, efficiency results are mixed and pretty low for the rest of the sample.

Table 4 Efficiency results using CCR input oriented model in the period from 2016 until 2021

Stock / Year	*2016*	*2017*	*2018*	*2019*	*2020*	*2021*	*Average*	*Std. Dev.*
CROBEX	94,99%	100,00%	100,00%	100,00%	65,53%	100,00%	93,42%	12,61%
CROBEXindu	48,20%	29,33%	28,98%	28,45%	50,14%	22,52%	35,29%	9,87%
CROBEXKons	35,48%	46,56%	7,03%	11,07%	6,21%	5,57%	18,28%	16,55%
CROBEXnutr	46,97%	28,36%	100,00%	18,91%	60,57%	71,93%	52,95%	26,36%
CROBEXturi	63,63%	100,00%	75,55%	92,36%	29,52%	33,03%	65,20%	27,58%
ADPL	42,12%	93,61%	31,84%	43,25%	30,19%	23,28%	43,76%	23,48%
ADRS	73,92%	100,00%	64,28%	100,00%	11,03%	43,94%	74,87%	31,84%
ARNT	30,06%	85,76%	100,00%	100,00%	24,78%	18,76%	59,06%	36,82%
ATGR	100,00%	56,32%	32,70%	58,92%	100,00%	63,00%	64,00%	27,20%
ATPL	17,61%	31,60%	8,29%	10,13%	18,78%	11,22%	16,27%	7,85%
DLKV	17,20%	21,77%	6,77%	8,07%	35,10%	2,11%	15,17%	11,08%
ERNT	40,30%	40,36%	33,65%	33,69%	67,27%	61,19%	44,68%	11,95%
HT	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	0,00%
KOEI	100,00%	69,19%	48,87%	39,83%	51,64%	30,78%	56,72%	22,64%

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KRAS	64,95%	44,35%	30,17%	38,47%	44,34%	100,00%	53,71%	23,21%
MAIS	31,83%	22,60%	50,20%	100,00%	31,27%	94,06%	54,77%	30,60%
PODR	50,00%	17,48%	59,45%	27,85%	52,73%	21,62%	38,19%	16,40%
RIVP	51,33%	17,51%	25,77%	17,59%	25,96%	19,80%	26,33%	11,71%
VLEN	11,06%	32,57%	8,80%	18,48%	49,06%	24,35%	24,05%	13,73%
ZABA	34,14%	24,11%	24,07%	22,58%	61,60%	23,82%	31,42%	14,10%
Average	52,69%	53,07%	46,82%	48,48%	45,79%	43,55%	48,41%	3,48%
Std. Dev.	27,72%	31,15%	32,32%	34,97%	24,98%	32,68%	30,96%	3,59%

Source: Author's construct based on Zagreb Stock Exchange trading data ZSE (www.zse.hr), and financial statements data in the period from January 2016 until December 2021.

In Table 5 efficiency results for the BCC model that assumes variable returns to scale are presented. The results are higher by the nature of the model, and if a stock was efficient in the CCR model, it will be efficient in the BCC model. Improvements in the efficiency results are seen across the board, however the touristic and nutrition indices show above average efficiency, as well as ATGR, ARNT, ADRS, KOEI or the biggest companies from touristic, nutrition and industry sectors.

Table 5 Efficiency results using BCC input-oriented model in the period from 2016 until 2021

Stock / Year	***2016***	***2017***	***2018***	***2019***	***2020***	***2021***	***Average***	***Std. Dev.***
CROBEX	100,00%	100,00%	100,00%	100,00%	78,90%	100,00%	96,48%	7,86%
CROBEXindu	63,07%	32,49%	30,33%	30,71%	60,40%	28,62%	40,94%	14,77%
CROBEXKons	100,00%	100,00%	7,41%	14,12%	100,00%	5,86%	54,57%	45,51%
CROBEXnutr	47,13%	28,54%	100,00%	70,60%	68,77%	100,00%	69,17%	25,95%
CROBEXturi	100,00%	100,00%	94,75%	100,00%	30,80%	33,38%	76,49%	31,46%
ADPL	81,46%	100,00%	42,86%	43,60%	37,79%	23,51%	54,87%	26,74%
ADRS	100,00%	100,00%	100,00%	100,00%	11,06%	65,14%	79,37%	33,09%
ARNT	71,94%	100,00%	100,00%	100,00%	28,03%	20,70%	70,11%	33,90%
ATGR	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	0,00%
ATPL	100,00%	100,00%	8,58%	10,44%	27,15%	100,00%	57,70%	42,72%
DLKV	19,26%	44,31%	8,62%	8,74%	50,41%	100,00%	38,56%	31,90%
ERNT	43,62%	40,90%	47,90%	100,00%	100,00%	100,00%	72,07%	28,00%
HT	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	0,00%
KOEI	100,00%	95,30%	48,97%	59,42%	55,63%	100,00%	76,55%	22,15%
KRAS	68,34%	45,89%	30,33%	100,00%	54,17%	100,00%	66,46%	26,25%
MAIS	31,87%	34,83%	71,36%	100,00%	37,40%	97,86%	62,22%	29,06%
PODR	50,18%	18,54%	100,00%	75,50%	54,08%	96,81%	65,85%	28,40%
RIVP	100,00%	100,00%	100,00%	17,83%	31,43%	23,59%	62,14%	38,06%
VLEN	58,59%	100,00%	9,62%	25,47%	100,00%	100,00%	65,61%	37,29%
ZABA	77,14%	24,53%	33,77%	22,67%	73,82%	27,13%	43,18%	23,12%
Average	75,63%	73,27%	61,73%	63,96%	59,99%	71,13%	67,62%	5,98%
Std. Dev.	25,96%	32,78%	37,20%	36,82%	28,26%	36,22%	17,19%	12,16%

Source: Author's construct based on Zagreb Stock Exchange trading data ZSE (www.zse.hr), and financial statements data in the period from January 2016 until December 2021.

5. Conclusion and Recommendations

In this paper the focus of was decision-making under risk from establishing the theoretical background of theories developed to explain human, and subsequently investor's decision-making under risk. Furthermore, the goal was to identify efficient (in terms of risk) investment options on the Croatian capital market using selected stocks and stock indexes. Efficiency results from non-parametric DEA methodology show that even among the most liquid stocks on the ZSE there are but a few investment options. While average weekly returns in the observed period were, lower than expected, general CROBEX index proved to be an efficient investment option in terms of risk minimization, which could be a viable investment strategy for retail investors. However, the use of static DEA models in this paper is suboptimal, the use of dynamic and stochastic models in future studies could be proven beneficial in gathering more insight on the investment options and strategies on a shallow and illiquid capital market such as the Croatian capital market.

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Appendix

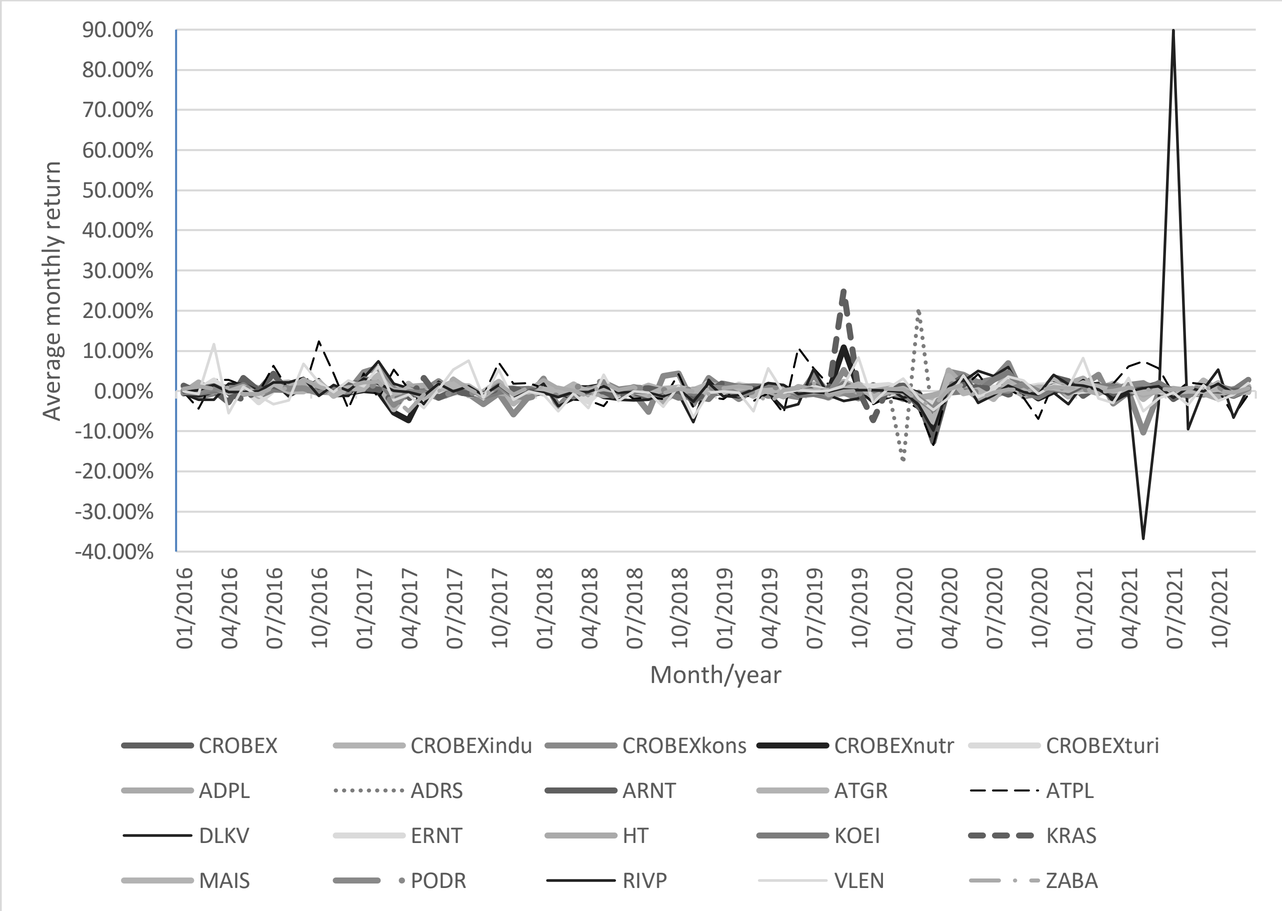

Figure 1 Monthly returns of selected stocks and stock indices on the ZSE in the period from January 2016 until December 2021

Source: Author's construct based on Zagreb Stock Exchange trading data ZSE (www.zse.hr) in the period from January 2016 until December

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