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STOCHASTIC DOMINANCE ON FTSE INDEX

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ABSTRACT. Stochastic dominance is a method that refers to a set of relations, which may hold between a specific pair of distributions. However, the concept can be applied in many domains, but in particular in financial economic areas, where the considered distributions are usually those of random returns to different financial assets. The aim of this paper is to provide an implementation of a stochastic dominance algorithm that establish which of more risky indices is preferred more by investors who have an aversive risk profile. The study is performed on FTSE indices. The focus is to emphasis the imbalance between FTSE regional indices and FTSE sectorial indices. The analyzed period for regional indices is April 3, 2000 –September 12, 2014. As regards the sector indices, the analyzed period is January 3, 1994 – September 12, 2014.Its relevance consist in that, it offers a different perspective for investors when choosing between different financial assets. This approach together with Meyer algorithm has been proved that it is a useful tool in risk aversion analysis.

Keywords: stochastic dominance, utility function, FTSE index

JEL Classification: C73, D9, D53

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I. Introduction

Stochastic dominance has been used in various forms since 1932, but this notion has been extensively employed and developed in different areas, such as economics, agriculture, marketing, finance, statistics, operations research, since 1969–1970. Many empirical and theoretical extensions of stochastic dominance in finance and economics were developed only after 1969-1970, when there were independently published four papers by Hanoch and Levy (1969), Hadar and Russel (1969), Whitmore (1970), Rothschild and Stiglitz (1970).

The approach of stochastic dominance is used in areas of choice under inequality and uncertainty measurement for a specific time, but having a reasonable degree of success. The first studies on stochastic dominance were limited only to one decision variable, which means that they could not analyze the effects of first stochastic dominance and second stochastic dominance on financial portfolio with more than three assets. Following the contributions of Rothschild and Stiglitz (1970, 1971) there were proposed many models in order to obtain specific results for optimal behavior of risk averse individual by using both first stochastic dominance and second stochastic dominance changes in returns distributions.

Stochastic dominance is a method of comparisons and it presents two important advantages. First advantage consists that all distinct features that characterize the analyzed distributions are showed in the ranking one obtains. Second advantage presents that the obtained rankings are in accordance with a big spectrum of value judgments captured by different proprieties of utility functions. This property was used to show that changes of distributions that increase equality and efficiency improve welfare.

This method has become a popular one with applications in stock markets, marketing, agriculture, political economy and industrial organization. For example, it allows to a manager of an insurance company the changed the offered contract without losing his customers. Also, stochastic dominance provides a way of ranking the risky alternatives without any detailed knowledge of the decision-maker preferences.

In this method, random returns are compared by using a point-wise comparison of performance functions that are constructed from their distribution functions. It is an analytical, easily implemented and intuitive tool, also uniquely suited to empirical output that is generated by different simulation models, including detrended fluctuation analysis. Furthermore, stochastic dominance represents a generalization of utility theory, eliminating the need to specify in a explicitly way the firm`s utility function. In some theoretical arguments, there is sometimes desirable to distinguish strong from weak stochastic dominance.

Hence, the rest of the paper is organized as it follows: the second section of this paper presents an overview on the existing work related to stochastic dominance, Section 3 illustrates its main theoretical principles regarding stochastic dominance, Section 4 presents the methodology of Meyer applied to stock markets, Section 5 shows the data used, Section 6 deals with a practical example meant to stress the advantages of this concept applied on FTSE regional indices and FTSE sectorial indices. In the end, a summary of results is presented and some conclusions are pointed out.

II. Literature review

Chen et al. (2010) investigate the possible January effect on stock market price in Singapore, Taiwan and Hong Kong, using daily data for the period 1990 – 2007. Trying to overcome the weaknesses of the most prior studies which used mean-variance criterion or Capital Asset Pricing Model (CAPM) statistics to test the calendar effects, they employ the stochastic dominance approach and the Davidson and Duclos test. Their empirical findings sustain the existence of monthly seasonality effects in these three Asian countries, but suggest that first order stochastic dominance for the January effect has mostly missing.

Başdaş Ü. (2011) examines the day-of-the-week effect for an emerging market, namely Istanbul Stock Exchange using a stochastic dominance approach. The empirical results indicate different outcomes independent of distribution assumption. The results reveal that Monday and Tuesday are not dominated by all other days of the week. Monday is dominated by only Wednesday, Thursday and Friday and Tuesday is dominated by Wednesday and Friday. Moreover, Friday is the day with the highest number of significant results, but it dominates all days, except Wednesday. On the contrary, Monday and Tuesday are the days with the least number of significant test results. Although, the results of stochastic dominance approach validate low Monday and Tuesday returns and high Friday returns, one single day can neither separately dominate other days of the week nor is dominated by other days. By contrast with previous studies that find a significant day-of-the-week effect for Istanbul Stock Exchange, this paper indicates that the day-of-the-week effect is limited in the Istanbul Stock Exchange.

McNamara J. R. (1998) suggests and assesses a precise statistical method for sampling the combinations on returns on applicant risky assets in order that stochastic dominance criteria can be used directly in an efficient linear programming model for portfolio selection. The sampling procedure uses the association of the return on every applicant stock with the return on a market index in a way similar to the Sharpe single-index model, thus removing the great number of combination with probability close to or matching zero. Portfolios estimated by the proposed linear programming stochastic dominance model are compared with those estimated by the single-index quadratic programming model, using 180 months for recent data on a sample of NYSE common stocks. The proposed method is aiming to complement existing mean-variance portfolio models for employ in circumstances in which it is suspected that the normal suppositions about returns on risky assets are not fulfilled, the suppositions about the utility functions of investors are too limiting, or when the intended portfolio must consist of a quite little number of assets.

In a paper supposed to be the first to employ stochastic dominance approach to analyze the Saturday effect, Al-Khazali et. al. (2010) realize an empirical investigation on weekend effect in three Gulf capital markets (Bahrain, Kuwait and, Saudi Arabia) from 1994 to 2006. They take into account the thin trading that is common in emerging equity markets. To explore the presence of the day-of-the week effect in analyzed stock markets, they use the stochastic dominance methodology that is not distribution-dependent and can highlight the utility and wealth inferences of portfolio choices by using information in higher order moments, Their empirical investigation show that the Saturday effect does not appear in the three emerging capital markets and that the stochastic dominance results indicate the Saturday effect in these three Gulf stock markets does not exist when raw data are corrected for thin and sporadic trading.

Using stochastic dominance analysis, Fang Y. (2012) examine whether the market portfolio is efficiently connected to benchmark portfolios created on size, value, momentum and reversal with diverse utility theories. Its finding sustain the prospect theory including the supposition of loss aversion at monthly and yearly horizon, which shows the market utility is S-shaped, and more abrupt for losses than for gains. Moreover, the results do not offer credible support for positive skewness preference. Thus, the author considers that it should investigate into asset pricing model and financial puzzles by prospect theory preferences. It could therefore be complicated for the market to profit from the asset through its characteristics on skewness or other higher order central moment. In order to testing stochastic dominance, the paper also expands a number of bootstrap procedures with positive features in statistical size and power.

Building a zero cost portfolios founded on second and third stochastic dominance, Clark E., Kassimatis K. (2014) reveal that they generate systematic, statistically significant, abnormal returns. These returns are robust relating to a range of conventional risk factors, including the single index CAMP, the Fama-French three-factor model augmented by a momentum, the Carhart four-factor model, and the liquidity five-factor model. Moreover, these abnormal returns are robust regarding to sample specificities, momentum portfolios, transactions costs, and varying time periods. The results are also robust as regards other risk factors, such as firm size, leverage, company age, return volatility, cash flow volatility, and trading volume. Their empirical results evidently prove that applying dominance relations as a supplementary filter for long and short positions can demonstrate profitable.

Adjusting the stochastic dominance test for risk averters recommended by Davidson and Duclos (2000) to be the stochastic dominance test for risk seekers, Qiao Z., Wong W.-K., Fung J. K. W. (2013) assume both tests to investigate the stochastic dominance relationship between stock indices and their corresponding index futures for 10 markets, including 6 developed countries and 4 developing economies. Their empirical investigation suggests that there should be no stochastic dominance relationship between spot and futures markets in mature financial markets in which arbitrage opportunities are infrequent and transitory. Though, they suppose that stochastic dominance relationship might be present in emerging financial markets that have more obstacles to arbitrage. Reliable with this conjuncture, their paper reveal that there are no stochastic dominance relationships between spot and futures markets in the developed markets, meaning that these markets could be efficient. By contrast, for the emerging markets spot dominates futures for risk averters, whereas futures dominates spot for risk seekers in the second-, and third-order stochastic dominance. Their findings show that there are potential gains in expected utilities for risk averters (seekers) when they change their investment from futures (spot) to spot (futures) in the emerging countries.

Hsieh and Chen (2012) study the existence of the day-of-the-week effect in the Taiwan Interbank Call Loan Market, applying stochastic dominance theory which is distribution-free, taking into account with and without risk-free asset. The results indicate that Monday days are associated with higher returns than all the other trading days of the week in the four diverse maturities, excepting overnight. Tuesday is associated with higher returns in the overnight maturity. Their empirical investigation also illustrate that allocating part of a financial institution’s funds in risk-free assets is useful in distinguishing returns among diverse trading days of the week. These evidences involve those financial institutions can have a better funds management, allocating an optimal quantity of investment in risky assets and risk-free assets.

To examine market portfolio efficiency relating to benchmark portfolio created on market capitalization, book-to-market equity ratio and price momentum, Post T., Levy H. (2005) apply diverse stochastic dominance measures that explain (local) risk seeking. Their findings indicate that stock returns can be explicated by reverse S-shaped utility functions with risk aversion for losses and risk seeking for gains. Moreover, the results are compatible with a reverse S-shaped sample of subjective probability transformation. They consider that low average yield on big caps, growth stocks, and precedent losers could be signs of investors' double desire for downside protection in bear markets and upside potential in bull markets.

For testing market efficiency, Bey R. P., Burgess R. C., Kearns R. B. (1984) proposed, and exemplified on a sample of stock splits, a new and more general methodology – moving stochastic dominance (MSD). Comparing this method with the cumulative average residual (CAR) risk-return analysis, they find that: 1) the constant CAR analysis results are similar with those of prior studies; 2) the moving CAR analysis results are diverging with the prior studies and show that investor are less wealthy after a stock split despite of the following dividend adjustment. Their MSD empirical investigation suggests that investors are almost equally wealthy despite of the following dividend adjustment.

Stochastic dominance approach can be also used to create indices for economic, political and financial risk, as suggest Agliardi E. et al. (2012). Using a stochastic dominance efficiency tests at any order, they build these indices in emerging market countries. They analyze tests for stochastic dominance efficinecy for a given risk index regarding to all possible indices constructed from a set of individual risk factors. The test statistics and the estimators are calculated employing mixed integer programming methods. Developing an economic, political and financial risk ranking of emerging markets, finally the authors construct an overall risk index. Their most important finding is that the sovereign risk environment in emerging countries can be primordially explained by the financial risk, followed by economic and political risk.

III. Stochastic dominance and applications

Generally speaking, the distribution of the return's assets are in general quite complex and is often hard to choose between them form a certain risk profile. There are many criteria to classify the dominance of an asset over another. From this point of view, this study is relaying on the order of dominance criterion. Theoretically, there is possible to have any order of dominance, but in practice, the characteristics of distribution will lead sometimes to an impossibility of stating the dominance order of one asset to another. Thus, there are defined the first order and the second order stochastic dominance, which could be frequently encountered in real applications. Hence, in the following parts there are presented the basic concepts related to these types of dominance.

An important application of previous concepts is found in are of stock markets and financial investments. In general, an investor acts similar a von Neumann individual from the utility point of view as described Meyer (2005) in his paper. Hence, the investor has to decide between two prospects (financial assets), *X* and *Y*, whose revenues or returns are randomly distributed. The investor will choose or will prefer the asset *X* instead of *Y* if:

$$E\{U(X)\} > E\{U(Y)\} \Leftrightarrow \int_0^A U(w)dF_X(w) > \int_0^A U(w)dF_Y(w) \quad (1)$$

where *X* and *Y* are considered random variables, defined on the interval [0; A]. Based on the utility function approaches, it is not very difficult to demonstrate that from a financial prospective $U'(w) > 0$, which simply means that any individual prefers more than less. Basically, if this property is verified, it is obtained the equivalent form of (1):

$$E\{U(X)\} > E\{U(Y)\} \Leftrightarrow \int_0^A U^{/}(w)[F_Y(w) - F_X(w)]dw > 0 \quad (2)$$

It is known also from McCarl (1999) that from an economical point of view the utility curve is characterized by its risk aversion function defined as:

$$-\frac{U^{//}(w)}{U^{/}(X)} = R(w) \quad (3)$$

Often in the literature it is used the concept of risk aversion coefficient, due to the fact that $R(w) = c$.

As stated by McCarl (1990) in his study concerning the Meyer algorithm, the choice for the preferred asset could be made by an investor for whom the utility function $U(w) = R(w)$ verifies the following constraint:

$$R_1(w) \leq R(w) \leq R_2(w) \quad (4)$$

Therefore, the integral presented in equation (2) has its maximum value if the following expression states true:

$$\int_0^A U^{/}(w)[F_Y(w) - F_X(w)]dw < 0 \quad (5)$$

Thus, any investor for whom the utility function verifies constraint (15) will choose the prospect Y rather than X. Hence, $E\{U(Y)\} > E\{U(X)\}$ means that *Y* dominates *X*.

In order to write the algorithm used to take the correct decision, it is important to notice that the risk aversion coefficient describes an ordinary differential equation of second-order, as stated in (3). Thus, for this kind of equation the initial condition – i.e.: $U'(0)$ needs to be known. On the other hand, a utility function is only defined by an infinite continuously and derivable transformation (function). In other words, the two functions $U(.)$ and $\widetilde{U}(.) = aU(.) + b$ describe the same investor's preference. Since $\widetilde{U}'(w) = aU'(w)$, it is possible to normalize the derivatives in a such a way that $U'(0) = 1$. Thus, the notation $V(w) = U'(w)$ is used.

Therefore, the described algorithm consists of two steps, as presented below. This algorithm is presented also in a similar way also in the research of McCarl (1990).

1) The first step consists in evaluation of the expression:

$$J^* = \max_{R_1(w)\le R(w)\le R_2(w)} \left\{ \int_0^A U^{/}(w)[F_Y(w) - F_X(w)]dw \middle| U^{//}(w) = -R(w)U^{/}(w), U^{/}(0) = 1 \right\} \quad (6)$$

2) The second step establishes which prospect (asset) is preferred accordingly with the value of J*. Thus if J* < 0 one will choose Y as a preferred asset (prospect).

The integral mentioned above, in the first step, does not appear to be an integral of optimal control. Therefore is needed another form this integral and also a resort to a change of the variable – i. e.: $U'(w) = V(w)$. Consequently, the integral will become:

$$J^* = \max_{R_1(w)\le R(x)\le R_2(w)} \left\{ \int_0^A V(w)[F_Y(w) - F_X(w)]dw \middle| V^{/}(w) = -R(w)V(w), V(0) = 1 \right\} \quad (7)$$

In order to maximize the integral describe in equation (6), there are needed the optimality conditions. The optimality conditions will lead to an achievement of the result, which conduct us to state which prospect is preferable in the detriment of the other one. The algorithm that finds the optimality condition is based on the Hamiltonian operator:

$$\begin{aligned} \mathrm{H} = {} & V(w)[F_Y(w) - F_X(w)] - \psi(w)[R(w)V(w)](w) \\ & + \lambda_1(w)[R(w) - R_1(w)] - \lambda_2(w)[R(w) - R_2(w)] \end{aligned} \quad (8)$$

Accordingly, this transformation applied to the equation (6) is leading to a rewriting of the integrals as it follows:

$$R(w) = \begin{cases} R_1(w) & \text{if} \quad \int_w^A [F_Y(s) - F_X(s)]U^{/}(s)ds > 0 \\ R_2(w) & \text{if} \quad \int_w^A [F_Y(s) - F_X(s)]U^{/}(s)ds \le 0 \end{cases} \quad (9)$$

Hence, if the function $R(w)$ is computed in an optimal way, then the rest of the algorithm consists only in evaluation of $J*$ and depending on its value, the dominance of one asset over another is determined.

IV. Methodology

We implemented the described algorithm in C# .NET programming language. The usefulness of this environment consists also in the fast development of applications, which involves matrices and others objects used for data storage and manipulation. Since the used time series are grouped in array and matrix, the software's utility is evident. Thus, we implemented the previous described approach in a software algorithm, which is applied for each pairs of studied variables (assets returns). Before fully describing the step-by-step implementation of the algorithm, we mention that each prices series for each analyzed index has been transformed in returns. Further, the return series has been transformed in histograms (distributions) in order to build up the probability repartition functions. Since the length of each data set is sufficient for computing the probability distribution function, we implemented an algorithm for automatic scaling of each data set accordingly to a predefined number of histograms bins. These functions are then applied as inputs to the Meyer algorithm.

The difficulty in the implementation of Meyer's algorithm lies in the fact that the function is defined by a forward integral and not by a backward integral as the usual integrals. For a better comprehension of implementing Meyer's algorithm, starting from empirical data, that we have $F_X(.)$ and $F_Y(.)$, we defined two constant functions in each discrete time interval. The functions are defined over one partition such as: $0 = w_0, \ldots, w_i, \ldots, w_N = A$ and $w_{i+1} - w_i = h$, where h is a small constant and N is the size of analyzed data. This parameter, has an acceptable value from the computational point of view, which can lead to achieve a good accuracy for the approximation of the integral obtained using a step with this (specified) value as it is described by Caliendo and Pande (2005) in their work related to optimal control.

Then, the expression $F_Y(w) - F_X(w)$ has to be derivated. Considering that $F_X - F_Y \geq 0$ in the interval $[w_{N-1}; w_N]$ and knowing that $U'(.) > 0$, then the following integral is positive:

$$\int_{w_{N-1}}^{w_N=A} [F_Y(w) - F_X(w)] U^{/}(w) dw > 0 \tag{10}$$

On this interval, $U'(w)$ verifies the differential equation $U''(w) = -R_1(w)U'(w)$, whose final solution for $w \in [w_{N-1}; w_N]$ is:

$$U^{/}(w) = U^{/}(w_N) e^{\int_w^{I_N} R_1(s)ds} \tag{11}$$

Although $U'(w_N)$ was not known from the beginning of algorithm, it is not very importance and it can be evaluate it arbitrarily. The contribution of the interval $w \in [w_{N-1}; w_N]$ for the optimal value of the target objective function (J^*) is given by :

$$J_1^* = \int_{w_{N-1}}^{w_N=A} [F_Y(w) - F_X(w)] U^{/}(w_N) e^{\int_w^{I_N} R_1(s)ds} dw \tag{12}$$

The next step in the algorithm is w_{N-2}, where it is also possible to calculate $U'(w_N)$ by using the discretized form of differential equation which defines $U'(.)$, as it follows:

$$U^{/}(w_{N-1}) = U^{/}(w_{N-2})(1 - R_j(w_{N-2})h) \Rightarrow$$

$$U^{/}(w_{N-2}) = \frac{U^{/}(w_{N-1})}{1 - R_j(w_{N-2})h} = \frac{U^{/}(w_N) e^{\int_{w_{N-1}}^{I_N} R_1(s)ds}}{1 - R_j(w_{N-2})h} \tag{13}$$

This allows the evaluation of the new integral:

$$J_2^* = [F_Y(w_{N-2}) - F_X(w_{N-2})] = \frac{U^{/}(w_N) e^{\int_{x_{wN-1}}^{I_N} R_1(s)ds}}{1 - R_j(w_{N-2})h} + J_1^* \tag{14}$$

At this point, one can make a choice for $R(w)$ based on the value of J_2^*. Thus, if $J_2^* > 0$ then $R(w_{N-2}) = R_1(w_{N-2})$, else if $J_2^* \leq 0$, then $R(w_{N-2}) = R_2(w_{N-2})$. Moreover, it is possible to calculate $U'(w_{N-3})$ and reiterate the operation until it is reached the step 0, for $U'(0)$. This allows deciding whether *X* or *Y* is dominant, for the two vectors data set, according to the presented approach.

V. Data

In order to test different aspects of stock exchange indices we use daily closing data of FTSE regional indices (FTSE Global 100 – FTSE G100, FTSE All-World Developed – FTSE-D, FTSE All-World Emerging – FTSE-EM, FTSE World Americas –FTSE-A, FTSE All-World Latin America – FTSE-LA, FTSE All-World Middle East & Africa – FTSE ME&A, FTSE World Asia Pacific – FTSE-AP, FTSE World Europe – FTSE-E) and FTSE sectorial indices (basic materials FTSE-BS, consumer goods FTSE-CG, consumer services FTSE-CS, oil & gas FTSE-OG, financials FTSE-F, health care FTSE-HC, industrials FTSE-I, technology FTSE-Te, telecommunications FTSE-Tl, utilities FTSE-U). All closing values of the indices are collected from Datastream database, respectively are denominated in local currency. The analyzed period for regional indices is April 3, 2000 –September 12, 2014. As regards the sector indices, the analyzed period is January 3, 1994 – September 12, 2014.

The main descriptive statistics of daily return series corresponding to FTSE Regional indices are presented in Table 1. We can observe that the mean return series are positive in all examined markets (exception being FTSE Europe), to the extremes being placed FTSE Middle East & Africa and FTSE Europe (which presents negative returns). A first argument that returns do not follow a normal distribution law is given by the Kurtosis coefficient (has higher values of 3), that means that the distribution is leptokurtic, which is much less sharp than the normal distribution, and by the asymmetry coefficient (Skewness) which is different from zero indicating a left asymmetry, i.e. – the left tail is larger.

Table 1. Descriptive statistics of return series of FTSE Regional indices

FTSE REGIONAL	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis
FTSE Global 100	0.000029	0.000368	0.1034	-0.0784	0.0109	-0.1837	7.7945
FTSE All-World Developed	0.000071	0.000593	0.0908	-0.0722	0.0106	-0.3154	7.6204
FTSE All-World Emerging	0.000256	0.000850	0.0968	-0.0982	0.0123	-0.5515	8.2133
FTSE Americas	0.000111	0.000510	0.1260	-0.1258	0.0143	-0.4642	9.4582
FTSE Latin America	0.000313	0.000929	0.1555	-0.1541	0.0173	-0.4252	9.9450
FTSE Middle East & Africa	0.000371	0.001014	0.0817	-0.1080	0.0140	-0.4263	4.1679
FTSE Asia Pacific	0.000042	0.000293	0.0980	-0.0991	0.0136	-0.5236	6.5344
FTSE Europe	-0.000016	0.000171	0.0931	-0.0807	0.0125	-0.1207	5.8603

Source: Own processing in Eviews

Note: Number of observations are 3704.

Return series for all FTSE Sectorial indices are positive, to the extremes being placed FTSE Health Care (0.032%) and FTSE Utilities (0.01%) (Table 2). Kurtosis coefficients are higher than the value of three, therefore the distributions are leptokurtic, and these do not follow the normal law. A remark useful in the experimental part, one can state that only distributions of FTSE Technology return indices have a right asymmetry, and for the other indices the distribution remains have a left elongated tail.

Table 2. Descriptive statistics of return series of FTSE Sectorial indices

FTSE Sectorial	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis
FTSE Basic Materials	0.00017	0.00042	0.0983	-0.1143	0.0125	-0.4949	10.2098
FTSE Consumer Goods	0.00021	0.00049	0.0935	-0.0579	0.0095	-0.0408	5.3279
FTSE Consumer Services	0.00019	0.00045	0.0792	-0.0724	0.0095	-0.2207	6.2076
FTSE Oil & Gas	0.00029	0.00069	0.1330	-0.1358	0.0129	-0.5404	11.6834

FTSE Financials	0.00012	0.00050	0.1131	-0.0970	0.0125	-0.1298	10.3615
FTSE Health Care	0.00032	0.00049	0.0993	-0.0628	0.0083	-0.2352	8.9733
FTSE Industrials	0.00024	0.00068	0.0716	-0.0794	0.0106	-0.3905	6.2656
FTSE Technology	0.00031	0.00081	0.1113	-0.0793	0.0151	0.0326	4.5116
FTSE Telecommunications	0.00014	0.00036	0.1005	-0.0780	0.0102	-0.1145	6.0868
FTSE Utilities	0.00010	0.00035	0.1248	-0.0791	0.0085	-0.1503	16.2651

Source: Own processing in Eviews

Note: Number of observations are 5400.

VI. Experimental Results

There are many important aspects in regards with the obtained results, which we want to point out in order to emphasis the relevance of the presented method. The stochastic dominance analysis is a concept that strongly relays on distribution of analyzed assets (prospects). The way in which this distribution is constructed has an important influence on the experimental results and some financial decisions. It is possible to build the distribution of the prices (value of indexes, in our case) or the distribution of the returns. If the price for a specific day (e.g.- let's say day *t*) is defined as P_t then the return is defined as: $R_t = \ln(P_t / P_{t-1})$. Apparently, there could be specific no interest to use one or another way of computing the distribution. Since the returns are presenting a higher interest in the stock market world and also due to the fact that the distribution of returns is close to a normal distribution (which could lead to a better econometrical modeling), we chose to use this representation as a basis for constructing the repartition functions for each of the analyzed index.

An interesting part of this analysis concerns to the risk coefficient values. We used only constant value for the risk aversion function since we considered that the lower and the upper limits bound the risk aversion in a proper way. For a proper analysis, we chose as a range for risk aversion coefficient the interval [-2;+2].

Hence, we present two tables, the first one is focusing on the results of FTSE Regional indices and the second one on the preferences of stock market players in regards with FTSE Sectorial indices. The tables are quite big since we grouped the results for all analyzed indexes. The value from each cell is representing the value for J^* measure described by (17).

Table 3. Generalized stochastic dominance for FTSE Regional indices

	FTSE G100	FTSE-D	FTSE-EM	FTSE-A	FTSE-LA	FTSE-ME&A	FTSE-AP	FTSE-E
FTSE G100	0							
FTSE-D	-7.82E-15	0						
FTSE-E	-2.93E-15	4.72E-15	0					
FTSE-A	-4.89E-15	2.83E-15	-1.95E-15	0				
FTSE-LA	-1.96E-15	5.67E-15	9.45E-16	2.84E-15	0			
FTSE-ME&A	0.002301	0.002297	0.002298	0.002303	0.002303	0		
FTSE-AP	0.002301	0.002297	0.002298	0.002303	0.002303	6.60E-15	0	
FTSE-E	-3.91E-15	3.78E-15	-9.74E-16	9.47E-16	-1.97E-15	-0.00235	-0.00236	0

Source: author's calculations in the own implementation software

The results presented in the previous table are reflecting the stochastic dominance in the preferences of investor with risk aversion for FTSE Regional indices. In this case, the period for each index has the same size. There are several aspects, which can be commented, since the information from the table can cover several topics. We just want to point out that the investors' preferences from the stochastic dominance point of view are in favor of stocks from Middle East & Africa and Asia Pacific. On the other side, it is possible to make a top of dominance, but one has to take into account that if the value of J_N^* for a certain asset is different compared with that obtained in case of other asset, the only which is taken into account is the sign. Unfortunately, this study is not covering also the topic related to size of J_N^*, which could lead to interesting conclusions to a refined result.

The situation changed as regard the sector indices, in the sense that there are more distributions that become dominant. A similar table with Table 3 is presented bellow in order to emphasis stock indexes' preferences in different areas of the economy.

Table 4. Generalized stochastic dominance for FTSE Sectorial indices

	FTSE-BS	FTSE-CG	FTSE-CS	FTSE-OG	FTSE-F	FTSE-HC	FTSE-I	FTSE-Te	FTSE-Tl	FTSE-U
FTSE-BS	0									
FTSE-CG	-0.0016	0								
FTSE-CS	0.001569	0.003136	0							
FTSE-OG	9.41E-16	0.001568	-0.0016	0						
FTSE-F	0	0.001568	-0.0016	-9.69E-16	0					
FTSE-HC	0.001569	0.003136	0	0.001574	0.001569	0				
FTSE-I	0	0.001568	-0.0016	-9.69E-16	0	-0.00161	0			
FTSE-Te	0.001569	0.003136	0	0.001574	0.001569	0	0.001566	0		
FTSE-Tl	0	0.001568	-0.0016	-9.69E-16	0	-0.00161	0	-0.00159	0	
FTSE-U	0.001569	0.003136	9.41E-16	0.001574	0.001569	9.43E-16	0.001566	9.39E-16	0.00157	0

Source: author's calculations in the own implementation software

It is interesting that there are situations when we cannot state exactly if there exists completely dominance between two distributions of the indices. There are situation when the change in sign indicate also a change in preferences of investors. We want to point out that the investors' preferences from the stochastic dominance point of view are in favor of stocks from the domains of consumer services, health care, technology and utilities.

The presented results from both tables are based on the same values for risk aversion coefficient. The coefficient values, which were suited to be used for a more precise analysis, were close to zero as indicated also the work of McCarl (1990). We tried to use a uniform approach so that for both type of indices the same values for risk coefficients have been used.

It could be seen that in regions from Middle East, Africa and Asia Pacific the changes in dominance are influenced by the higher volatility, which characterizes these markets. In these cases the structure of volatility that has a strong randomly character and the influence of the crisis had a higher impact on the preferences of investor with high aversion at risks.

VII. Conclusions

There are many applications of stochastic dominance concepts. Some of them are frequently encountered in finance and economics. Although, the stochastic dominance was applied in the early phase of this concept in economics and agricultural economy for various (random) variables, the recent studies covering topics like portfolio optimization and assets dominance for different levels of risk. Therefore this concept is recommended as a good risk measurement approach.

The changes in preferences for certain stock index are reflecting by the change in sign of stochastic dominance measure proposed by Meyer and implemented in our approach.

Stochastic dominance is measure of uncertainty, which apparently involves simple methods, but for a more complex analysis more advanced mathematical and statistical tools are required. The approach used in this paper, the Meyer algorithm is a good tool, which offers the possibility to have an overview of the possible preferences of individuals with aversion to risk. The results are relevant in the sense that this approach could be successfully used in the process of financial decision-making.

The latest researches that are suing stochastic dominance as decision tool are indicate this method as a good approach, which could be used in other areas of financial markets, especially in wealth and portfolio managements. Therefore, the presented approach could be enhanced by implementing some methods, which construct portfolios composed of different assets and the analysis should be performed in order to optimize the constructed portfolios.

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REFERENCES

Agliardi E., Agliardi R., Pinar M., Stengos T., Topaloglou N., 2012. A new country risk index for emerging markets: A stochastic dominance approach, *Journal of Empirical finance,* 19, pp. 741 – 761.

Al-Khazali O., Zoubi T. A., Koumanakos E. P., 2010. The Saturday effect in emerging stock markets: a stochastic dominance approach, *International Journal of Emerging Markets*, Vo. 5 No.2, pp. 227-246.

Başdaş Ü., 2011. The day-of-the-week effect for Istanbul stock exchange: a stochastic dominance approach, *Journal of Applied Finance & Banking*, vol.1, no.4, pp. 233-238.

Chen W. N., Hsueh Y.-H., Chen Y.-T., Chang C., 2010. Investigating Seasonal Anomalies in Asian Stock Market Prices: A Stochastic Dominance Approach, *International Journal of Management*, Vol. 27 No.1, pp. 144-152.

Clark E., Kassimatis K., 2014. Exploiting stochastic dominance to generate abnormal stock returns, *Journal of Financial Markets,* 20, pp. 20–38.

Fang Y., 2012. Aggregate investor preferences and benefits in stock market: A stochastic dominance analysis, *Journal of Empirical Finance,* 19, pp. 528-547.

Hadar, J., Russell, W.R., 1969. Rules for orgering Uncertain prospects, *American Economic Review*, vol. 59, pp. 25-34.

Hanoch, G., Levy, H., 1969. The efficiency analysis of choices involving risk, *Review of Economic Studies*, vol. 36, pp. 335-346.

Hsieh, C.-S., Chen C.-T., 2012. Using stochastic dominance criterion to examine the day-of-the-week effect, *Applied Financial Economics*, 22, pp. 1207–1213.

McCarl, B.-A., 1990. Generalized Stochastic Dominance: An empirical examination, *Southern Journal of Agricultural Economics,* 22(2), pp. 49- 55.

McCarl, B.-A., Besseler, D.-A., 1999. Estimating an upper bound on the Pratt risk aversion coefficient when the utility function is unknown, *Australian Journal of Agricultural Economics*, Vol. 33 (1), pp. 56 – 63.

McNamara, J. R., 1998. Portfolio selection using stochastic dominance criteria, *Decision Sciences,* 29(4), pp. 785-801.

Meyer, D., Meyer, J., 2005. Risk preferences in multi-period consumption models, the equity premium puzzle, and habit formation utility, *The Journal of Monetary Economics,* 8, pp. 1497–1515.

Meyer, J., Orminston, M.B., 1985. Strong Increases in Risk and Their Comparative Statics, *International Economic Review*, vol. 26, pp. 425 – 437.

Post T., Levy H., 2005. Does risk seeking drive stock prices? A stochastic dominance analysis of aggregate investor preferences and beliefs, *The Review of Financial Studies*, 18(3), pp. 925 – 953.

Qiao Z., Wong W.-K., Fung J. K. W., 2013. Stochastic dominance relationship between stock and stock index future markets: International evidence, *Economic Modelling,* 33, pp. 552 – 559.

Rothschild, M., Stiglitz, J., 1970. Increasing risk: A definition, *Journal of Economic Theory*, vol. 2, pp. 225-243.

Rothschild, M., Stiglitz, J., 1971. Increasing risk: Its economic consequences, *Journal of Economic Theory*, vol. 3, pp. 64-84.

Whitmorer, G.A., 1970, Third degree stochastic dominance, *American Economic Review*, vol.60, pp. 457-459.