ESG FUNDS VERSUS STOCK MARKET:

DYNAMICS OF EMPIRICAL RELATIONSHIP IN THE USA

by

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LIST OF ABBREVIATIONS

ADF Augmented Dickey-Fuller test

AIC Akaike Information Selection Criteria

ARCH Autoregressive Conditional Heteroscedasticity

ARMA Autoregressive Moving Average

ARIMA Autoregressive Integrated Moving Average

CBOE Chicago Board Option Exchange

ECM Error Correction Model

ECT Error Correction Term

EGARCH Exponential GARCH

ESG Environmental, Social, Governance

GARCH Generalized Autoregressive Conditional Heteroscedasticity

IRF Impulse Response Functions

MSCI Morgan Stanley Capital International

OLS Ordinary Least Squares

SIC Schwarz Information Criterion

S&P Standard and Poor's

SRI Sustainable, Responsible and Impact

TRESGUS Thomson Reuters US Large Cap ESG Index

USA United States of America

VAR Vector Autoregressive

VIX Volatility Index based on S&P 500 index

VECM Vector Error Correction Model

CHAPTER 1. INTRODUCTION

According to the US SIF Foundation (2018) in 2017 about $12.0 trillion was allocated into sustainable, responsible and impact (SRI) investment instruments only in the U.S. capital markets, which is 38 percent more compared to $8.7 trillion in 2016. In fact, environmental, social or corporate governance (ESG) securities, which are getting more involved in modern asset management constituted $11.6 trillion of total SRI assets, which is 44 percent more than $8.1 trillion in 2016.

The new practice of taking into consideration not only returns, but environmental, social, and governance problems in investing has evolved rapidly from its origins in the monitoring of publicly-traded companies on the basis of ethical values. ESG stands for Environmental, Social, and Governance. Investors are increasingly applying these non-financial attributes as an essential part of their analysis routine to measure risks and investing opportunities.

Although moral issues are not easy to assess in monetary terms and they do not enter common financial metrics, the share of socially responsible and sustainable investing is expected to have constituted about 50% of all professionally managed assets in the USA by 2025. According to BNP Paribas ESG, globally, the percentage of both retail and institutional investors that apply environmental, social, and governance (ESG) principles to at least a quarter of their portfolios jumped from 48 percent in 2017 to 75 percent in 2019 ("ESG Global Survey", 2019).

Nevertheless, the United States got engaged in the ESG assets management mostly in 2019. Flows into sustainable funds have expanded to US$8.9 billion through the first half of 2019, compared to US$5.5 billion in whole 2018.

The modern portfolio theory states that investor maximizes his/her wealth by allocating funds into the market portfolio, but not individual stocks, and chooses a particular risk-award combination through borrowing and lending at the risk-free rate. Thus, on no account, 'green' portfolio could be a subset of the assets' universe that give higher returns than the market portfolio does. It brings us to a question: if there is a driving force that makes investors shift to responsible investing, does it necessarily mean irrationality or an investor can benefit from both responsible and conventional strategies? We are not aiming at analyzing the behavior of a 'pure' ESG investor who has no tolerance towards non-ESG assets and thus, investing in 'green' instruments only is their ultimate decision regardless of the level of returns and risks that follow such strategy. Moreover, it requires background knowledge of the investor's individual preferences, which cannot be generalized to the group of investors that are trying to balance between wealth maximization and impact investing or thinking about allocation the funds in ESG assets as an alternative investment decision with a marginal tradeoff.

This thesis conducts a comparative analysis of the dynamic linkage between market portfolio riskiness and ESG-portfolio riskiness during the two equal five-year periods starting from February 2010, when a global economy had passed the financial crisis and started its recovery, until nowadays. There is also an outlook of this linkage after the COVID-19 outbreak followed by the stock market crash on February 19, which is studied separately. Although the market indices contain ESG instruments and the pairwise correlation between portfolios is there, dynamic relationship analysis can give a piece of insightful information about the co-movement of indices through time and volatility spillover between them.

Therefore, the main question of this study is: "Is there a change of the dynamic linkage between the stock market and ESG portfolio in the USA throughout the past decade?".

This study has important implications for different types of investors and other agents that operate in the U.S. stock market. In particular, a pure ESG investor can observe market movement to forecast returns of his/her portfolio if the cointegration between stock market benchmarks and ESG portfolio is evident. Although ESG investing is the ultimate decision for such an investor, he/she can use knowledge of market behavior for strategic planning and risk assessment. An investor who wishes to shift to responsible investing or partially reallocate his/her funds into ESG equities can find diversification properties of the ESG portfolio if there is no co-movement between market and sustainable portfolio. This knowledge is essential if one wants to achieve a marginal tradeoff in terms of returns and risk employing ESG criteria as a part of the investment strategy. At last, arbitrageurs who aim at getting risk-free profit can benefit from evidence of stock market benchmarks and ESG portfolio cointegration. Despite having little interest in the fundamental value of particular securities, they are active participants of the stock market and help it achieve efficiency. Betting on the divergence spread of cointegrated funds and waiting until they converge is beneficial regardless of market trends: bullish, bearish, or following sideways.

In addition, a lot of studies support that stock market co-movement is of considerable interest to policy makers from a perspective of the effects on the macroeconomy, the planning of monetary policy and impact of the degree of stock market co-movements on the stability of international monetary policy. Anyhow, an absence of cointegration between funds allows to estimate a short-run linkage which may also be insightful when it comes to searching for diversification opportunities by an investor.

Another part of dynamic linkage analysis studied in this thesis is the volatility spillover phenomenon. This is an open secret that all traded funds are subject to shocks caused by the news, investors' expectations, etc. Therefore, if there is a volatility spillover happening between two funds, the fluctuations in one asset could be caused by the unexpected innovations in another one. It is beneficial for an investor holding both funds to be aware if such spillover effect is temporary or long-lasting to set his or her holding period horizon.

CHAPTER 2. LITERATURE REVIEW

Globalization processes and free capital mobility have widened opportunities for investors. However, more and more investors are apt to allocate their funds not only by geography but also due to ethical considerations. The modern portfolio theory suggests that assets should not be weighed by their risk-reward proposition individually but, rather, by how each asset fits into an overall portfolio (Markovitz, 1952). For this reason, assets that are available in the stock markets are usually analyzed in terms of indices, hypothetical portfolios of investment holdings. Although sustainable investing is more broad activity than ESG investing, given that it mostly constitutes of the latter assets, the terms 'sustainable' asset and 'ESG asset' will be used interchangeably.

Sustainability (ESG) indices, like conventional stock market indices, are indicators of the price trends the most representative shares in a stock market reflect (Escrig-Olmedo, Muñoz-Torres and Fernández-Izquierdo, 2010). Discussions about whether responsible investing strategies help or worsen investment performance are complicated by the fact that there are several wide categories of responsible investing practice and they affect portfolios in different ways (Caplan, Griswold, Jarvis et. al., 2013). Nevertheless, there is a great number of papers that study and compare indices and their linkages across economies and markets by different attributes, such that prices, returns, historical and implied volatilities, etc. Dynamic linkages analysis enables one to extract insightful information about indices, thus markets, short-term and long-term behavior and possible steady states, which are equilibriums making separate markets adjust to each other over time.

Investors will be able to have well managed portfolios, if they have knowledge about financial integration (Joshi, 2011). Ample studies have been done to explore cointegration phenomenon. In addition to short-run and long-run linkages of investment returns, many studies have investigated the volatility linkages, in particular, across currencies, oil and commodities prices. Although, we focus on the stock market and ESG-market in the USA in our research, it is essential to follow a neat methodology applied in academic studies in macroeconomics, statistics and market analysis, etc.

Le, Thai-Ha and Chang (2011) using vector error correction (VEC) approach find in their study that one may observe movements in gold price to predict fluctuations in interest rates in Japan.

Within developed economies, Chong et al (2003) reveal that the Australian market has short-term and long-term relationship with the United States of America. Using the vector autoregressive (VAR) model while analyzing Japan, France, UK, Germany markets resulted in little evidence of cross-dependence.

Bouri et al. (2017) used implied volatilities of gold, oil and the Indian stock market to examine cointegration amongst three highly important in India markets. It is a well-established fact that implied volatility indices not only reflect historical volatility data, but also investors' expectation on future market conjuncture (Liu et al., 2013).

Given the absence of options trading with ESG-index as an underlying asset, we are only able to estimate inter-dependence between indices using realized volatilities. There is a list of well-accepted approaches in volatility modeling and its further examination. Statistical time series models are frequently applied in financial data analysis. ARCH, GARCH, EGARCH, TGARCH models are employed to model and forecast volatility which is non-constant over time and financial series shows that it is indeed highly sensitive to the news, geopolitical events and other shocks.

Similar research questions on volatility were also initiated among macroeconomists who studied causality of macro indicators through their volatilities. Haque and Kouki (2009) examined the effect of 9/11 to financial market using GARCH framework and concluded that there was correlation increase amongst developed economies over time.

Beltratti and Morana (2006) had investigated the relationship between stock market and macroeconomic volatility using S&P series and revealed the causality mostly goes from stock market to macroeconomic indicators and is much weaker in the opposite direction.

It is also important to review studies from the field of socially responsible investing since we are aiming at filling the gap in this area. The modern portfolio theory tells us that the variability-award pair of any feasible portfolio never lies above the capital market line (CML) in the variability-award space, obtained by combining the risk-free asset and the portfolio that maximizes the Sharpe ratio (Markovitz, 1952). Thus, the available literature is focused not on testing whether the ESG portfolio as a part of tangency portfolio can outperform the market portfolio but revealing its impact on the whole market or diversification opportunities gained by allocating funds into ESG assets.

For example, de Souza Cunha and Samanez (2013) explored the socially responsible portfolios in terms of their risk and award. A comparative study of SRI and market portfolios demonstrates that the SRI fund fails to provide a better financial yield.

Hoepner (2010) was trying to detect how the inclusion of ESG characteristics into investment portfolios affect the selection of the stocks that an investor can choose from, their correlations, and if it brings additional risk in those stocks. It was concluded that the integration of ESG criteria worsens portfolio diversification.

Sadorsky (2014) employed vector GARCH models to study the variability and conditional correlation between a stock price index comprising of socially responsible companies, oil prices, and gold prices and concluded that social and responsible investment is comparable to investing in the S&P 500.

Berry & Junkus (2013) and Lewis & Mackenzie (2000) claimed environmental considerations are a more important factor of ethical investing than religious and corporate governance driving forces.

The ESG and financial asset classes was investigated in terms of Granger causality by Andersson and Hoque (2019). Their findings mainly suggest that there are significant causal linkages between ESG and the other assets, in particular, ethical and traditional commodities and currency regardless of investment horizon.

Granger's causality model, auto-regressive conditional heteroskedasticity (ARCH)-GARCH framework were used to find the inter-dependence between the markets in the study of Jain, Sharma, Srivastava (2019). They checked and confirmed and evidence of the bi-directional volatility spillover between the 'green' indices and the MSCI conventional indices during 2013-2017 period using Vector Error Correction Model.

The majority of the papers on socially responsible investment opportunities studied mutual funds and their financial performance. The socially responsible mutual funds have been in the center of many studies, while the sustainable indices had not been receiving the same level of attention among academicians (Fowler and Hope 2007).

Due to the rapid expansion of the field of ESG investing and because of its relative novelty, there may be a lack of papers that study ESG performance features and especially with regard to other portfolios. Natarajana, Singh, Priya (2014) claim that for many investors it turns out to be a solid strategy to maintain a long-term horizon and ignore the short-term fluctuations, which is in line with our research goal.

Motivated by the work of Bouri et al. (2017) who focused on the nonlinearities between the implied volatilities of commodities and stock indices, we will investigate realized volatility linkage between stock index and ESG index and its change with time.

Therefore, our paper aims to study the volatility of the ESG index and the volatility of the conventional market index, and whether these two indices are interdependent in a non-constant way. With the emphasis that we are not targeting any evidence that ESG class assets can outperform market portfolio either in terms of risk or by an award but concentrating on the strength and possible change of linkage between two, we want to fill a least some gap in the available literature. As discussed earlier, the USA picked up the pace of ESG investing mostly in 2019, thus an increase in the share of ESG assets in the total assets' universe could potentially lead to changes in the impact of sustainable indices on the market as a whole. We believe that after 2017 when a similar comparative analysis was conducted by Jain, Sharma, Srivastava (2019) the discussion on promoting ESG considerations among traded equities was of a lower scale. In addition, not only the returns, but also the volatilities and their spillover are placed in the center of this paper due to the investors' concerns about unprecedented stock market fluctuations nowadays.

CHAPTER 3. METHODOLOGY

This research analyzes the volatility spillover of US stock market benchmarks and an ESG index fund along with a dynamic linkage between the latter and the benchmarks. S&P500 index which is well accepted as the best reference of large-cap U.S. equities, RUSSELL2000 which represents small-cap equities, and NASDAQ Composite (NASDAQ) which consists of 3000 securities listed on the Nasdaq stock exchange are studied. As ESG index fund Thomson Reuters US Large Cap ESG Index (TRESGUS), which is published by S-Network and calculated on the capitalization-rating basis, is taken. According to Thomson Reuters Corporate Responsibility Indices Methodology (2013) half of the weight of TRESGUS assigned to each stock within a sector is based on float market capitalization and half of the weight assigned to each stock within a sector is based on the stocks relevant rating. These three benchmark indices are chosen since they include equities of different capitalization and are the most followed market portfolios.

The volatilities modeling is conducted at the first stage, here the study focuses on the comparative analysis of their evolution during three studied sub-periods. The first two periods together cover a decade (5 years each) starting from the early 2010 when the world economy got over the financial crisis. A third period is discussed next as an outlook of nowadays reality of the U.S. stock market and covers post-COVID outbreak starting from February 19 of this year till October 22, however, this sub-period is not directly compared to the first two in this study due to significant difference in sample size and unprecedented lockdown that caused a crash of the U.S. stock market in February 2020. Next, Johansen cointegration methodology is employed to test indices for possible cointegration, which allows to choose appropriate vector model to estimate the dynamic relationship between funds, either VAR or VEC. This study does not follow Engle-Granger methodology because it runs linear regression of series and uses estimated residuals to conduct cointegration test. Usually, such test is less efficient than Johansen cointegration test. Finally, after estimating appropriate vector model the Impulse-Response functions are estimated as a volatility spillover between chosen funds. IRF shows how much and how long an unexpected shock in one asset can influence another asset. At the end the estimated volatilities and volatility spillover dynamics between indices are analyzed both graphically and numerously. The weakness of this approach is that the estimations come from different models and conventional VAR or VEC do not allow to model the volatilities inside the model. However, following the literature the study compares output from different models, such as ARIMA-GARCH and VAR/VEC, given that the models comply with pre-estimation and post-estimation requirements. Among pre-estimation tests are Augmented Dickey-Fuller test for series stationarity check, Autocorrelation and Partial Autocorrelation functions for detecting Moving average and Autoregressive processes in a univariate series of each index, Johansen cointegration test. Among post-estimation tests there are ARCH Engle's test for heteroscedasticity check in ARIMA model, Ljung–Box test for diagnosing explanatory power left in the residuals, stability test for vector models for checking whether all eigenvalues of the matrix lie within a unit circle, Lagrange Multiplier test for autocorrelation check.

For the purpose of this study, a heteroscedasticity is discussed as a volatility clustering phenomenon, series with no explanatory power and no process detected is considered white noise, and terms 'stationary' and 'mean-reverting' can be used interchangeably.

This paper uses data both in levels and in logarithmic differences (returns) since the time series models such as ARIMA and VAR require stationary series as an input, but Johansen cointegration test and VEC model use raw non-stationary data. To arrive at the daily continuously compounded return, a natural logarithm of the current index price to the previous index price ratio is taken, which is given by the formula:

$$I_T = I_t * e^{\mu(T-t)}$$

$$\mu(T-t) = \ln(I_T) - \ln(I_t) = \ln\left(\frac{I_t}{I_{t-1}}\right) \tag{1}$$

In equation 1, μ represent index return per unit of time, I_T represents index price at time T, I_t represents index price at time t, (T-t) represents time increment which is positive.

To proceed with econometric analysis of volatility, the data is first visualized using the graphs. Then, an Augmented Dickey-Fuller (ADF) unit root test is conducted to check if the series are stationary or not. The basic concept of this test is given by the formula:

$$r_t = c + \pi * r_{t-1} + \psi * \Delta r_{t-1} + \eta_t \tag{2}$$

In equation (2), r_t represents today's return, r_{t-1} represents yesterday's return, Δr_{t-1} represents yesterday's first difference of the returns.

A unit root test is conducted both for the level and returns series. In order for data to be stationary, π has to lie within a unit circle; whenever it is equal to 1, data is no stationary and requires differencing. It is common for the financial series such as stock and indices prices to follow a random walk, meaning they are non-stationary in nature and the best prediction for today's value is yesterday's one. Stocks and indices series are said to be difference stationary as they require only one differencing to get stationary. Nevertheless, a general pre-estimation methodology is followed regardless of such properties of financial data.

The series further are fitted into an ARIMA model, which is necessary to control for autoregressive and moving average processes present in the return's series. Autocorrelation function (ACF) and partial autocorrelation function (PACF) are used to identify the number of AR and MA lags. ACF shows how many lags of residuals to include into the model, which is the MA process, while PACF represents the number of lags of the index values to include, which is the AR process. The most appropriate model is chosen based on the AIC and SIC values. The lower the value the better the model is.

After all useful information is extracted from the data, the test for ARCH effect, ARCH Engle's test, is conducted. Financial data are frequently characterized by volatility clustering, which means that plotting the squared residuals of ARIMA gives an understanding that volatility is not constant over time. The ARCH effect measures the risk of an asset which helps reveal the time-varying phenomenon in the conditional volatility. The most appropriate model of the ARCH family is chosen based on AIC and SIC values. This study is not aiming at choosing among all possible ARCH family models but is checking if an Autoregressive Conditional Heteroscedasticity (ARCH) specification is a better fit than a Generalized Autoregressive Conditional Heteroscedasticity GARCH specification. The difference between these two is that the ARCH model estimate volatility based on the lags of squared residuals and the GARCH model also includes a conditional volatility component. An advantage of the latter model is ability to avoid overparameterization which is usually observed in ARCH model that may require many lags of squared residuals to utilize the volatility clustering. Often a GARCH (1,1) specification is used to model financial series volatility.

Finally, the volatility series of S&P500, RUSSELL2000, NASDAQ, and TRESGUS returns for all three periods are extracted from the fitted models. The volatility series are visualized and compared throughout the studied periods.

In order to estimate the linkage between the market benchmarks and TRESGUS series, it is necessary to find whether there is only a short-run interdependence among variables, or a long-run equilibrium is also present. At the first step ADF unit root test is conducted. For stationary data series the long-run relationship does not exist. In this case vector autoregressive (VAR) model in levels is used for further analysis. It is not the case for stocks and indices data in levels as these series are typically non-stationary. In case of non-stationarity, there is a potential cointegration between series. The presence of cointegration allows to predict difference between two assets which is mean reverting and stationary in nature. This amount to effectively creating a so-called synthetic asset which is nothing else but a stationary combination of two non-stationary series, and whose value can be quite accurately predicted. The analysis of a long-term linkage of non-stationary multivariate time series has been carried out by cointegration methodology suggested by Johansen and Juselius (1990). This methodology consists of two main tests: Maximum Eigen Value test and Trace test. The tests are conducted using non-stationary raw series which is values of indices. In the model with one lag, VEC equation for indices series is represented by the following form:

$$\Delta I_t = c + \xi * z_{t-1} + \varphi * \Delta I_{t-1} + \eta_t \tag{3}$$

In equation (3), I_t represents current indices levels vector, Δ represent the differencing operator, and t-1 represents the lagged observation, z represents cointegrating equation

If $\xi = 0$ then there is no cointegration. For the bivariate model to have an error correction term (ECT) the rank of ξ should be equal to 1.

An absence of cointegration means there is no long-run convergence between assets and the difference between those is not predictable. Despite this, they still may have short-run relationship and cause fluctuations in each other. VAR model of returns is estimated for better results interpretation even though non-stationarity issue is solved by simple differencing of the series.

At last, impulse-response estimation is conducted to find evidence of volatility spillover. Under volatility spillover, the change of one index fund in response to the unexpected shocks in another one is meant. However, this relationship does not have to be bidirectional, and the shock in one of two indices may not find its reflection in the value of another. IRF shows the magnitude and duration of such volatility spillover and represented as 100%-to-k% change meaning that 100% of unexpected shock in one asset increases/decreases daily returns of another one by k percent.

CHAPTER 4. DATA

The core dataset contains two periods formed by two series of 1265 observations of S&P500, RUSSELL2000, NASDAQ, and TRESGUS daily prices each and third smaller period of 135 observations rolling from the stock market crash on the 20th of February 2020 until today.

Daily closing prices of both indices are taken for the ten years from the 1 February 2010 to 19 February 2020 and divided for two periods, from 1 February 2010 to 10 February 2015 and from 11 February 2015 to 19 February 2020 respectively, which is in line with the period selection in the available literature, where five-year data periods are typically used (Alexandre and Francisco 2018; Ortas et al. 2014; la Torre et al. 2016). Only trading days are included in the dataset. Moreover, by 2010 the economy of the US had come out from the global financial crisis and started growing, which sets the second period aparts from the first one. Additionally, the series beginning from the 20 February 2020 are collected for further analysis as during this short period an unprecedented event took place and broke stock markets all over the globe.

Data analysis begins with the descriptive statistics which includes the presentation of mean, Shapiro-Wilk statistic, and minimum-maximum values. Raw data of indices in levels is not helpful as it is not directly comparable. In order to get comparative insights first of all the descriptive statistics of the daily returns is computed and represented in the Table 1.

Table 1. Descriptive statistics of non-annualized daily returns, %

	February 2010 – February 2015			
	S&P500	RUSSELL2000	NASDAQ	TRESGUS
Mean	0.051	0.053	0.039	0.047
Minimum	-6.896	-9.332	-7.149	-6.933
Maximum	4.632	6.713	5.159	4.607
S-W Test[1]	0.9417***	0.9562***	0.9570***	0.9438***
St Dev[2]	0.0100	0.0141	0.0113	0.0103
	February 2015 – February 2020			
Mean	0.039	0.027	0.061	0.036
Minimum	-4.184	-4.504	-7.149	-4.196
Maximum	4.840	4.844	5.159	4.686
S-W Test[1]	0.9343***	0.9783***	0.9570***	0.9416***
St Dev[2]	0.0084	0.0102	0.113	0.0086
	February 2020 – October 2020			
Mean	0.0111	-0.0282	0.0962	-0.0043
Minimum	-12.765	-15.399	-13.149	-12.878
Maximum	8.968	8.976	8.935	10.009
S-W Test[1]	0.9093***	0.9324***	0.9126***	0.9238***
St Dev[2]	2.5776	3.1844	2.6314	2.7067

[1]Shapiro-Wilk Normality Test. Null hypothesis: the population is normally distributed,

*** indicates 1% significance level, [2] Standard deviation

A Z-test for the statistical difference between mean returns in the first period and mean returns in the second one results in no rejection of the null hypothesis for each index fund. It means on average none of the two periods stands out in terms of financial performance of the stock market in the USA. The returns of the Covid-19 period is not tested since one has much fewer observations unlike previous samples that are independent and equal in nature.

As the modern portfolio theory suggests market portfolio gives a better risk-award combination that any portfolio formed of a subset of all assets available on the exchange. Nevertheless, the gap between S&P500 and TRESGUS portfolios is relatively small, while RUSSELL2000 and NASDAQ are of larger range in the first period. In the second period NASDAQ is the one to have a range of daily returns more than 10% on a non-annualized basis. All series are normally distributed. The last studied period is associated with drastically higher uncertainty, daily standard deviation of returns reached about 3% and the highest daily loss exceeded 12.5% on a non-annualized basis for all indices and reached 13.4% on a non-annualized basis for RUSSELL. However, during this period a rapid improvement took place and the highest daily returns reached 9% for all indices and beat 10% for TRESGUS which is twice as much as in the previous periods. To sum up, the Covid-19 outbreak is the one when the studied ESG index fund beats the market when it is boolish and loses the least when the market is bearish.

Figure 1 presents an evolution of four studied index funds starting from February 2010. Some convergence in the spread of pair indices could be expected, however visual inspection is not reliable approach while searching for long-run equilibriums between assets.

Figure 1. Consolidated graph of the indices during the studied period

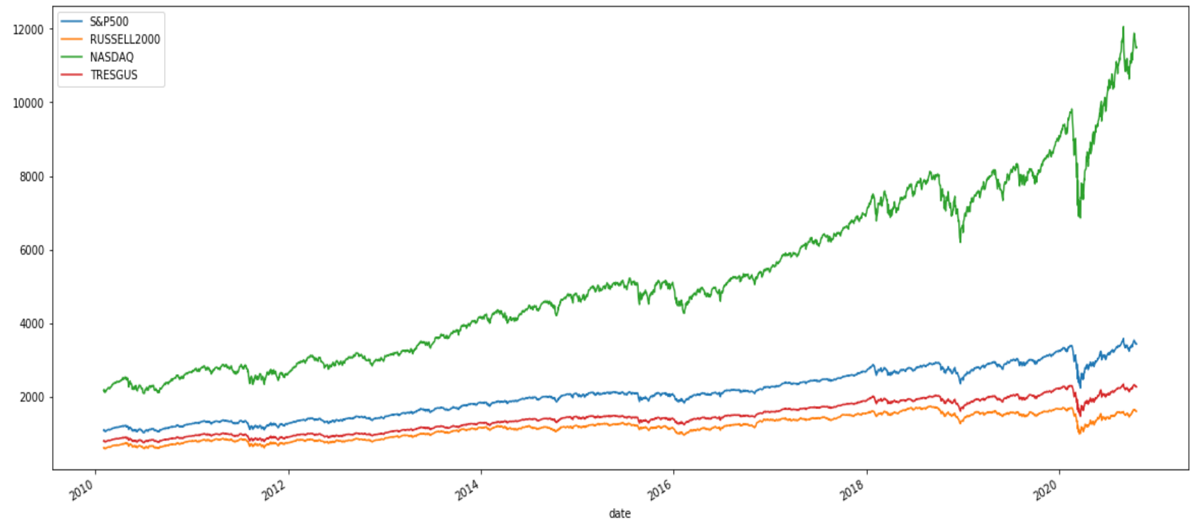
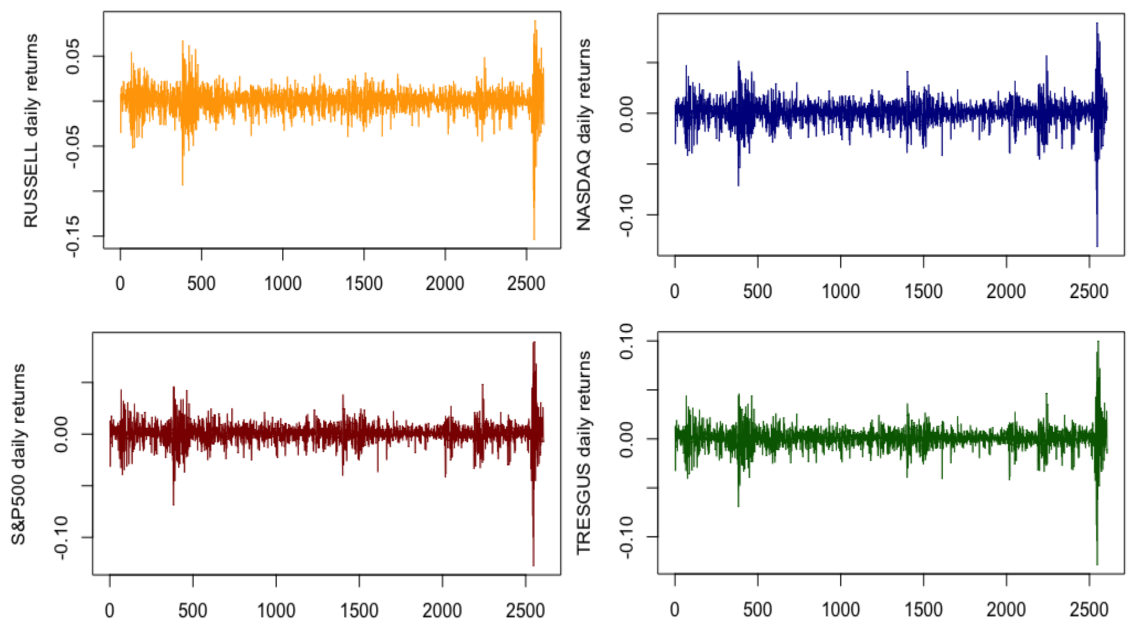


Figure 2 presents the combined graph of daily returns of four studied indices during three subperiods from 2010 till nowadays. It is evident that the indices have volatility clustering throughout the concerned time period (two out of three periods as of now). There is also some interdependence to be observed, however TRESGUS turns out to be slightly more volatile and of lower returns that S&PP500. Yet RUSELL2000 and NASDAQ represent the larger range than the other two. COVID-19 outbreak followed by the stock market crash on February 20 is evident on all four plots. Even though the returns naturally seem to be mean reverting it can be seen that the volatility is clustered during the times of economic instability.

Figure 2. Consolidated graph of the indices returns during the studied period



The results of ADF testing of indices daily returns are presented in the Table 2 for each of three periods separately.

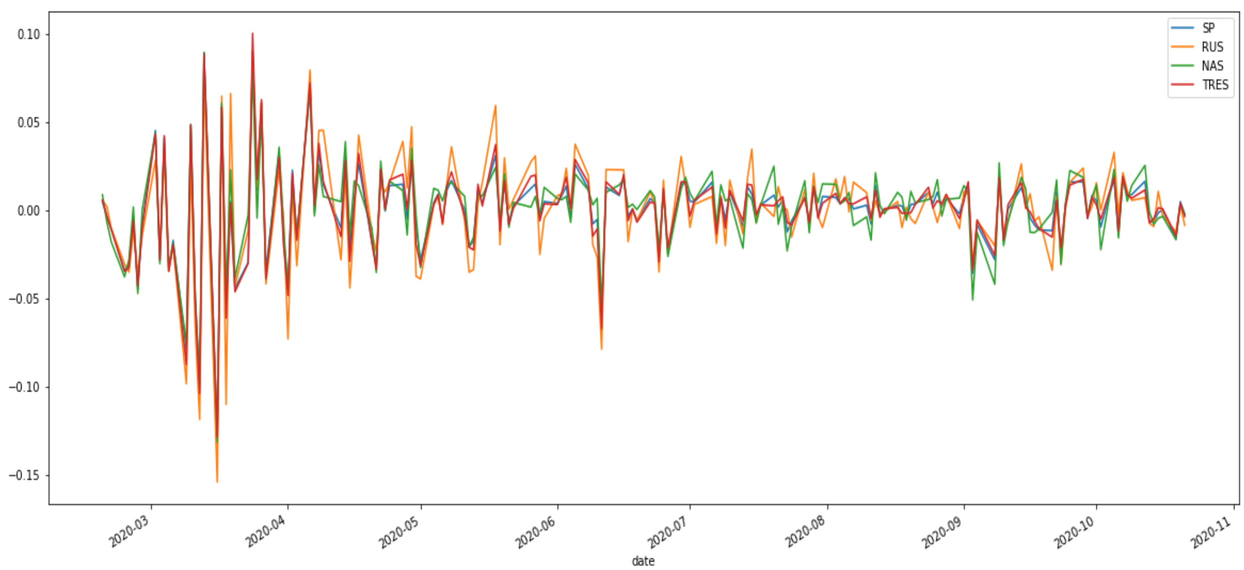
Table 2. Augmented Dickey-Fuller (ADF) test results

	February 2010 – February 2015			
	S&P500	RUSSELL2000	NASDAQ	TRESGUS
Number of lags[1]	4	21	4	4
DF statistic	-18.37	-8.93	-17.91	-18.33
p-value	<0.01***	<0.01***	<0.01***	<0.01***
	February 2015 – February 2020			
Number of lags[1]	1	0	7	1
DF statistic	-26.71	-35.66	-13.77	-26.49
p-value	<0.01***	<0.01***	<0.01***	<0.01***
	February 2020 – October 2020			
Number of lags[1]	8	6	8	8
DF statistic	-3.32	-4.58	-3.52	-3.35
p-value	<0.1***	<0.01***	<0.01***	<0.1***

[1]Lag-order selection number based on AIC value

The null hypothesis of unit root presence is rejected at 99% confidence level. All returns series for the first and second periods are stationary meaning they are I(0) and don't require differencing to be used in the econometric model. Thus, ARMA model which is equivalent to ARIMA with d=0 is estimated and tested for ARCH effect presence later in Chapter 5. The last period differs from the previous ones as a period of instability and large fluctuations, see Figure 3.

Figure 3. Post Covid-19 outbreak returns of studied indices



During the third period returns are stationary at 95% confidence level.

Although the volatility modeling is conducted using stationary data, in particular, daily returns, Johansen cointegration test is applied to non-stationary indices series in levels. In the presence of cointegration indices series in levels are used to estimate relationship between indices using VEC model, while in the absence of cointegration, the daily returns are taken for further dynamic linkage estimation using VAR model.

CHAPTER 5. RESULTS

5.1. Volatility modeling

At the first stage, the volatility of each index is modeled. TRESGUS is compared with every of the stock market benchmarks which are widely followed by investors in the USA. Interestingly, an ESG index fund has a behavior similar to S&P500. The two follow the same Autoregressive Moving Average (ARMA) process throughout the studied periods. It can be because of both funds embrace large-cap U.S. equities and have a significant overlap with each other. It might create a problem in the inferences; however, we might treat TRESGUS a filtered and improved version of the S&P500 index fund. On the contrary, the processes followed by RUSSELL2000 and NASDAQ are not the same in all periods due to different compositions.

The volatility clustering is evident from the visual inspection of the daily returns data. In addition, test for an ARCH effect is made. The results of univariate ARIMA-GARCH analysis for the first period are represented in the table 3. The results for other two periods are shown in Appendix 1.

Table 3. ARIMA-GARCH modeling results, Feb 2010 – Feb 2015

	S&P500	**RUSSELL2000**	**NASDAQ**	**TRESGUS**
AR 1	-0.061*	-0.8693*	-	-0.8352*
AR 2	0.046*	-	-	-
AR 3	-0.063*	-	-	-
MA 1	-	0.8005*	-	0.7800*
Alpha 1	0.020*	0.092*	0.015	0.022*
Alpha 2	0.100*	0.0995*	0.1084*	0.100*
Beta 1	0.8799*	0.8796*	0.8561*	0.8800*
AIC	-8386.22	-7533.75	-8045.87	- 8333.36

*indicates 99% confidence level

In table 3 AR represents autoregressive process, MA represents moving average process, Alpha 1 is a constant, Alpha 2 represents conditional variance, Beta represents squared residuals, and numbers represent lag order.

After the models are fitted, volatility series is extracted as a sigma of the model and then annualized, which in conventional for financial analysis. Figures 4 and 5 plot the annualized volatilities of indices in the following order: S&P500, RUSSELL2000, NASDAQ, and TRESGUS throughout first and second period respectively.

Figure 4. Estimated annualized volatilities of index funds, Feb 2010 – Feb 2015

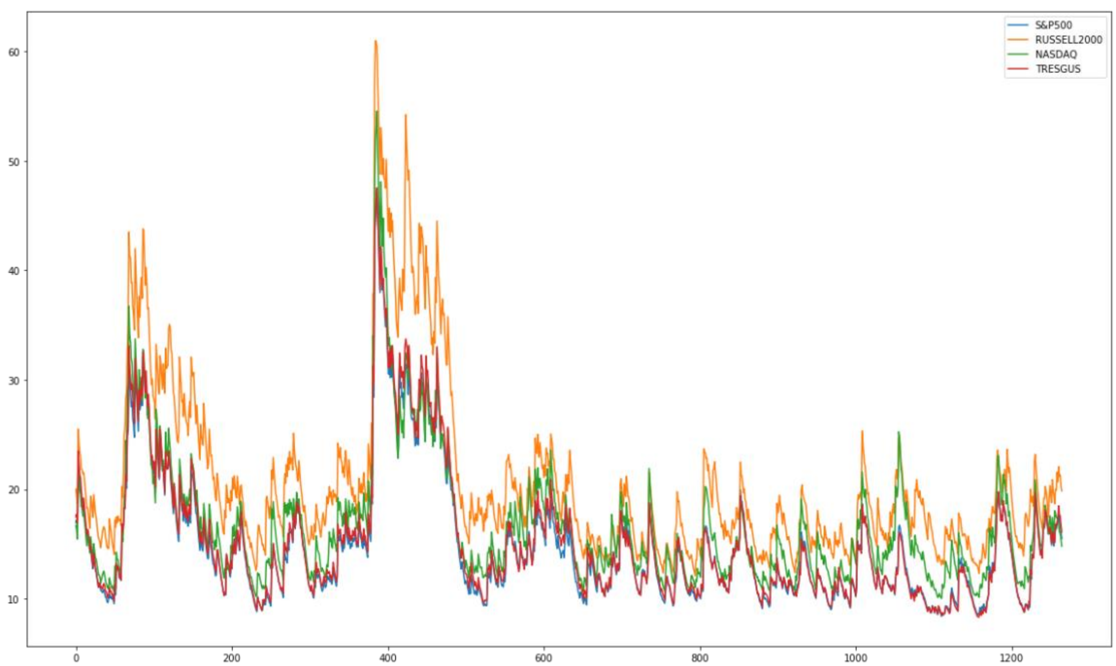


Figure 4 represents that the high-volatility period of 2010 and 2011 was followed by the calming of the market fluctuations further on.

Figure 5. Estimated annualized volatilities of index funds, Feb 2015 – Feb 2020

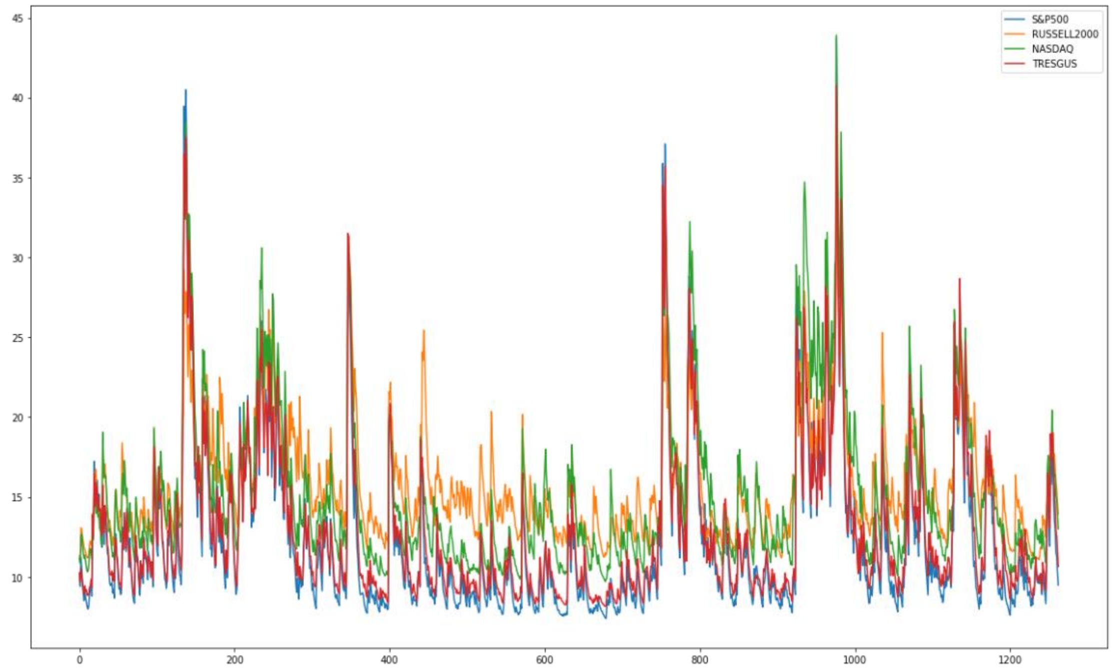
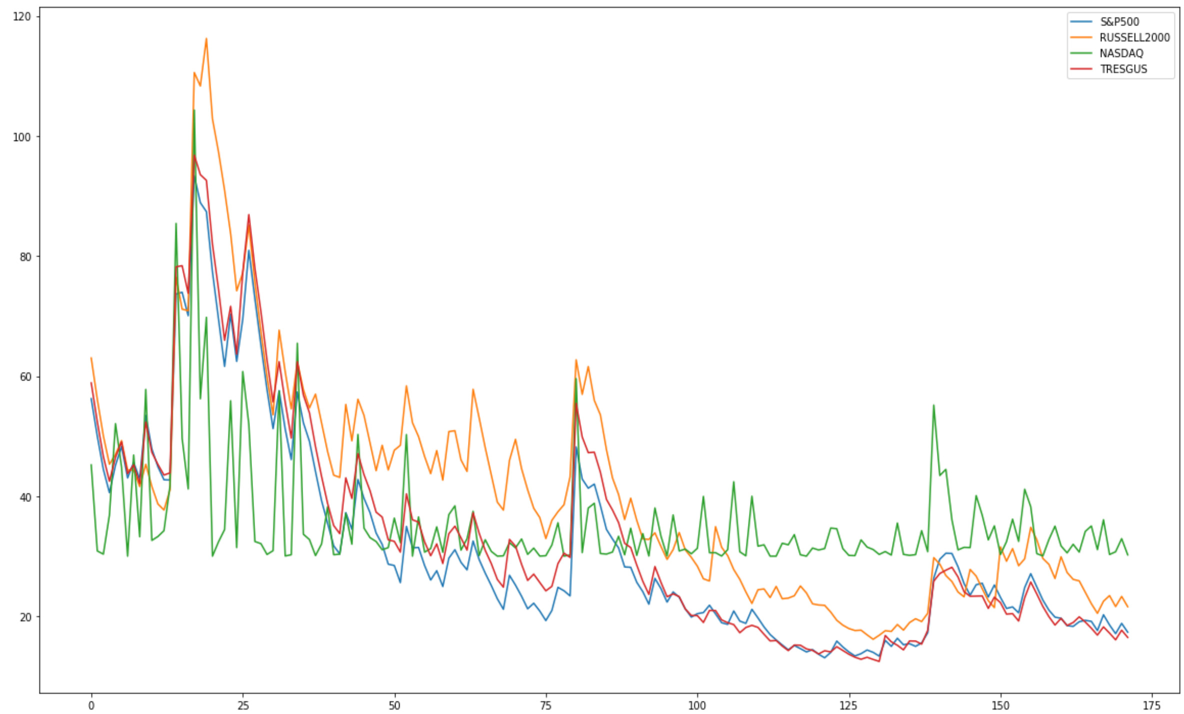


Figure 5 shows that over the second period the spikes of fear did not exceed 45% on the annual basis. Generally, as can be seen there is a significant similarity in indices variability. Since TRESGUS follows market trends, a presence of dynamic linkage between it and three benchmarks is expected. During the time of high uncertainty S&P500 and TRESGUS volatilities reached similar new highs of 47.5% during the first period, while RUSSELL2000 and NASDAQ volatilities were 69% and 54.8% respectively. Unlike first period, the second period was featured by larger highs of S&P500 and TRESGUS whose volatilities exceeded 40%, while NASDSAQ calmed down to 43% in terms of volatility and RUSSELL got the least volatile with maximum of 36.1% over the period. The minimum volatilities were similar for all index funds and fluctuated around 10%.

After Covid-19 outbreak the stock market behavior was unusual, so was the volatility of the studied indices.

Figure 6. Estimated volatilities during February 20th – October 22th, 2020, %



It is evident that the stock market crash on the 20th of February was followed by abnormal volatility period, the highest annualized volatility reached 100% for all indices in March and almost beat 120% for RUSSELL2000. Nevertheless, starting from April benchmarks started cooling off and approaching to their minimum volatility as of August 2020. An ESG index was not the one with lowest volatility and cannot be treated as the least risky index fund to invest in.

5.2. Johansen cointegration methodology

At the first stage, Johansen cointegration test is conducted for TRESGUS-S&P, TRESGUS-RUSSELL, TRESGUS-NASDAQ pairs. It is often used given its robustness towards the similar Engle-Granger test.

Table 4. Johansen cointegration test results

	S&P500	RUSSELL2000	NASDAQ	Critical value*
		February 2010 – February 2015		
Test statistic	-1.39	-2.50	-2.56	-3.91
		February 2015 – February 2020		
Test statistic	-1.64	-1.67	-2.86	-3.91
		February 2020 - October 2020		
Test statistic	-4.09	-3.38	-3.71	-3.96

*indicates 1% significance level

Neither first period nor second period was featured by cointegration between ESG index and the stock market benchmarks. In particular, the null hypothesis of no cointegration cannot be rejected given the estimated p-values for each pair. Additionally, trace test is run and resulted in 0 rank of the matrix for the two studied period and confirms absence of cointegration. Therefore, VEC cannot be estimated and VAR is the chosen model. Bivariate Vector Autoregressive Models (VAR) are run and the estimates are represented below in the table 5. However, the test results in the evidence of cointegration between indices after Covid-19 outbreak. Thus, VEC is employed for the third period. We cannot employ VAR for the modeling the third period because a long-run equilibrium should appear in the model equations.

Table 5. Pairwise VAR models between TRESGUS and the benchmarks

		February 2010 – February 2015	
TRESGUS as endogenous	S&P500	RUSSELL2000	NASDAQ
L	-.97	-.04	-.13
L2	-.56	-.02	-.07
L3	-.03	-.11	-.14
L4	.02	-.03	-.01
L5	-.22	-.09	.01
		February 2015 – February 2020	
L.	-.02	.06	.08
L2	-.26	.05	-
		February 2010 – February 2015	

TRESGUS as exogenous	S&P500	RUSSELL2000	NASDAQ
L	-.86	-.02	.10
L2	.56	.06	.15
L3	-.08	.14	.15
L4	-.05	.03	.04
L5	-.19	-.07	-.12
		February 2015 – February 2020	
L	-.05	-.04	-.15
L2	.21	-0.08	-

In the table 5 L represents lag operator, * indicates significance level 5% or lower. TRESGUS as endogenous variable means that the index return is the variable of interest in the autoregressive equation. TRESGUS as exogenous variable means that the index return is an independent variable in the pairwise equation. Each equation consists of the pair ESG-benchmark. Three benchmarks do not appear in the same equation.

Table 6. Pairwise VEC models between TRESGUS and the benchmarks

		February 2020 – October 2020	
TRESGUS as endogenous	S&P500	RUSSELL2000	NASDAQ
L	-1.13	.45	-.04
L2	-.71	.66*	-.01
L3	-	.46	-
L4	-	.24	-
L5	-	.84*	-
L6	-	.48	-
ect	.52*	-.27*	0.01*
TRESGUS as exogenous	S&P500	RUSSELL2000	NASDAQ
L	1.66	-.45*	-1.09
L2	1.79	-.39*	1.29
L3	-	-.19	-
L4	-	-.23	-
L5	-	-.51*	-
L6	-	-.58*	-
ect	.66*	-.28*	.04

In the table 6, ect represents error correction coefficient which is a speed of divergence. It should lie between -1 and 0 so the adjustment happens, otherwise vector relationship is explosive in nature and capturing the equilibrium is not feasible. An interpretable model is fitted for the TRESGUS-RUSSELL pair. Those are linked both in the short and in the long run with almost the same speed of adjustment, about 28%.

To summarize, there is no interdependence between TRESGUS returns and each of the benchmarks' returns evident only during the first and second studied periods. During the Covid-19 period the ESG index fund and RUSSELL2000 depend on each other. In particular, the latter positively affects TRESGUS and TRESGUS negatively affect the benchmark. Those are also sharing the long-run equilibrium and adjust to each other. The remaining pairs do not seem to have either short-run interdependence or a long-run divergence.

After parameters estimation all fitted models are validated against post-estimation requirements: residuals are white noise and normally distributed, there is no autocorrelation and the model is stable (eigen values lie within unit circle).

5.3. Impulse-Response relationship

At last, the volatility spillover as a response of one index to the shock in another one is analyzed. It is found that the volatility spillover, which is the thing that reflects responses of one index to shocks in another index, exists (table 7).

Table 7. Impulse-response between TRESGUS and the benchmarks, %

		February 2010 – February 2015	
TRESGUS response[1]	S&P500	RUSSELL2000	NASDAQ
Day 0	-0.9	-0.11	-0.12
Number of days[2]	10	11	9
		February 2015 – February 2020	
Day 0	-0.25	0.06	0.08

Number of days[2]	5	5	2
	February 2020 – October 2020		
Day 0	-0.6	0.5	-0.05
Days 10-50	3.2	-1.5	0.3
Number of days[2]	-	-	-
	February 2010 – February 2015		
TRESGUS impulse[3]	S&P500	RUSSELL2000	NASDAQ
Day 0	0.8	0.14	0.15
Number of days[2]	11	10	11
	February 2015 – February 2020		
Day 0	-0.01	-0.07	-0.15
Number of days[2]	3	3	2
	February 2020 – October 2020		
Day 0	1	-0.75	-1
Days 10-50	-6.1	1.3	-3.2
Number of days[2]	-	-	-

[1]Reverting from the mean per shock in a pair index

[2]Until full stabilization (the response = 0) to the shock

[3]Shock in TRESGUS that causes respective % change in benchmark

As it is evident all periods are featured by a unique volatility spillover between the studied indices. During the second period the spillover coming from the shock in the benchmarks took almost twice less days till the pair ESG index got irresponsive. Moreover, the magnitude became lower meaning that TRESGUS response could be disregarded whenever an investor held both ESG index fund and the benchmark index fund longer than a business week for pairs with S&P and RUSSELL, and two trading days for NASDAQ. Shocks in TRESGUS caused increase in the benchmarks during the first period and decrease during the second period. However, those impulses-responses became as short as 2-3 business days. Innovation in TRESGUS did not lead to significant changes in S&P during the second period.

The third period turned out to be very unstable. None of the impulses in the ESG index found its stabilization in the benchmarks and vice versa. A few inferences can be made due to the size of the dataset and potential presence of some hidden factors.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

This research provides us with several important insights. Firstly, there is no evidence that the long-run equilibrium exists between ESG benchmark and market ones. This means that one cannot forecast ESG portfolio dynamics observing a stock market movement and vice versa. Moreover, a short-run interrelation is also not evident for all three pairs during the first two periods. For an investor, no causality between the studied ESG index and stock market portfolios is beneficial when he or she is seeking for diversification opportunities. Investing in the TRESGUS index fund means adopting responsible approach with little or no sacrifice in terms of diversification since the market benchmarks do not influence ESG benchmark.

Interestingly, during the Covid-19 period the studied funds seem to share a long-run equilibrium. An ESG index and RUSSELL share both short-run and long-run dynamics. It means that a stock market agent can predict movements in the 'responsible' fund observing movement in the small-cap market while the remaining pairs' linkage is not insightful.

The short-run and long-run relationship between two funds are not the only metrics of interdependence between two or more stocks an investor should be aware of. Such phenomenon as volatility spillover between assets may impact risk and return whenever an innovation or any shock in one asset is a case for another asset in a pair or portfolio that is responsive to such event. It is found that the volatility spillover is stronger for the pair TRESGUS-S&P500 that can be explained overlap in their compositions. Generally, impulse-response relationship gives insights on how to adapt trading or investing strategy in terms of duration of taken position and expected stabilization. Thus, during the first period it took TRESGUS from 9 to 10 days to get over the shock coming from the market portfolios. During the second period the duration of TRESGUS both impacting the market and responding to the market shrank a lot: one could expect stabilization within 5 trading days after a shock coming from S&P500 and RUSSELL and only 2 days after a shock coming from NASDAQ. This means that the diversification property of the studied funds is still there, yet the investment horizon for an investor or a position duration for a trader are the things to be reconsidered. In particular, calming down period in the event of a shock either in the ESG index fund or the benchmark halved. Thus, an agent can set spot agreements on the day after the shock occurrence while other market participants going less risky or putting their positions on hold. That is why impulse-response analysis is valuable even for the assets that are not cointegrated or cause each other.

However, a stabilization of TRESGUS which means getting irresponsive after shock occurrence in the market during the post Covid-19 outbreak is not evident. Given that the interrelation did not appear between S&P-TRESGUS and NASDAQ-TRESGUS pairs there is a chance that the estimated volatility spillover is spurious, and one should come up with looking for hidden factors. Otherwise, a single market shock launches a volatility spillover to the ESG index fund for more than 50 days which is a suspicious in nature event.

Finally, it is evident that during the period of high uncertainty after Covid-19 outbreak the variability of TRESGUS exceeded that of S&P500 and NASDSAQ. This suggests that the ESG index is not a less risky asset than the market portfolio.

To sum up, the ESG portfolio, represented by TRESGUS, can be beneficial in terms of diversification for an investor holding small-cap market portfolio, represented by RUSSELL2000, and tech market portfolio, represented by NASDAQ Composite due to no causality present between each pair. It takes shorter to get stabilized after innovations for TRESGUS-NASDAQ and NASDAQ-TRESGUS than for TRESGUS-RUSSELL and RUSSELL-TRESGUS, however traders with position duration more than 5 business days could disregard such difference during 2015-2020 period up to COVID-19 outbreak. The direction of a response to the impulse is also not important for an agent willing to hold his or her portfolio over a sufficient period. This knowledge can decrease an investor's fear and help to avoid his/her excessive boolish or bearish expectations against ESG index fund. It is also important for an investor or a trader to become knowledgeable about the linkage between the 'responsible' benchmark and the small-cap benchmark. Given that those do not overlap in terms of their constituents yet are strongly dependent on each other both in the short and long run, one may dig deeper and analyze what characteristics of the small-cap index affect the ESG fund of large-cap companies.

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APPENDIX

Table 8. ARIMA-GARCH modeling results, Feb 2015 – Feb 2020

	S&P500	**RUSSELL2000**	**NASDAQ**	**TRESGUS**
AR 1	-	-	-	-
MA 1	-	-	-	-
Omega	0.0006*	0.0001*	0.0007*	0.0009*
Alpha 1	0.227*	0.130*	0.153*	0.200*
Beta 1	0.676*	0.773*	0.769*	0.700*
AIC	-8847.34	-8104.76	-8276.46	-8739.54

Table 9. ARIMA-GARCH modeling results, Feb 2020 – Oct 2020

	S&P500	**RUSSELL2000**	**NASDAQ**	**TRESGUS**
AR 1	-1.13*	-1.29*	-1.14*	-1.09*
AR 2	-0.02	-0.26	-0.05	0.04
AR 3	0.335*	0.28*	0.28*	0.34*
MA 1	0.896*	1.17*	0.88*	0.92
MA 2	-	0.41*	-	-
Omega	0.0006*	0.0001*	0.0007*	0.0009*
Alpha 1	0.200*	0.200*	0.35	0.200*
Beta 1	0.780*	0.780*	-	0.780*
AIC	-897.78	-803.58	-822.03	-892.18