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CONNECTIONS BETWEEN SENTIMENT INDICES AND REDUCED VOLATILITIES OF SUSTAINABILITY STOCK MARKET INDICES

Abstract*. Capital markets provide the framework for the evaluation of a wide selection of issues, ranging from investors' psychological profiles to likelihoods of various expected long-term, i.e. sustainable scenarios. Using a large class of models from the GARCH family to estimate conditional volatilities, we perform a comparative analysis of the dynamics of risks for two classes of indices: on one hand the sustainability indices, built as portfolios of companies active in the fields of sustainable development, and on the other hand a series of regular stock market indices, used as benchmarks for regular economic performance. We found clear evidence that the risk of benchmark indices, measured using many volatility models from the GARCH family is larger than the ones characterizing the sustainability related counterparts. This paper shows that that these differences in volatilities exhibit explanatory power for economic sentiment indices employing a MIDAS methodology that allows for the connection of time series with different frequencies.*

Keywords*: volatility; sustainability indices; stock market; high-frequency data; MIDAS regression.*

JEL Classification: G17, G32

1. Introduction

The importance of capital markets for the field of sustainable economics is well supported by a large group of academic papers that rely on their ability to achieve a sound evaluation of both historical dynamics as well as consensual perspective of economic implications. The usual objective of these analyses is to highlight the importance of sustainable development activities for long term growth in general and prove the resilient nature of these activities by assessing them in comparison with the rest of the economy as a whole. The objective of this paper subscribes to the latter group of investigations by analyzing the extent to which financial market participants are considering the long-term nature of the sustainable activities as being less risky.

Under the assumption that asset prices reflect the market participants' views on the information about economic environment as a whole, we consider that the dynamics at various frequencies should reflect these views. The differences in the perceived risks for these two classes of assets should be explained by the confidence exhibited by market participants in the sustainability related financial assets. The consistency of these differences could qualify them as clear candidates for the long-term investment institutions like the pension funds and insurance funds and offer the possibility of international portfolio diversification in search for a higher risk-adjusted performance. At a fundamental level, which takes into account the theoretical connections between economic efficiency and ecological sustainability, we mention here the work of Pan (1994) that studies the assumed conflicting perspective of these two concepts. Based on the use of an optimal control model, the article provides an investigation that suggests the fact that ecological sustainability could be realized with economic efficiency. Based on this conjecture we can consider that the sustainability equity indices used in our paper contain a strong reflection of the concept of sustainability in market participants' beliefs.

Financial markets are also used as communication channels in the sense that managers try to disclose information that will increase the value of their companies. As this value depends on market participants' beliefs in the possible growth of listed companies, the information disclosed might determine the inclusion in larger portfolios. A stream of research demonstrates the fact that in the process of revealing information about their inside operations, companies tend to allocate an important weight to a selection of sustainability related activities. Gurvitsh and Sidorova (2012) provide evidence in this respect for the importance of Corporate Social Responsibility issues in a series of companies listed at the Tallinn Stock Exchange in an economy in which they prove that financial reports constitute an important element in performance assessment. Another direction deals with the issue of unclear perception of the meaning of sustainable operations. Comyns et al. (2013) investigates the features of a high quality report on sustainability related issues by suggesting that the type of information is an important element in the establishment of the quality of a report. A related stream of research covers the importance of the stock market performance from the perspective of sustainability related financial assets. Mollet and Ziegler (2014) compares the general performance of stock markets with that associated to the socially responsible investing. Employing a four-factor model they prove that this type of investment does not provide significant performance improvement due to the fact that the companies promoting this type of sustainable investment are usually large companies, i.e. diversified portfolios. In a study that investigates the particular case of Brazilian listed companies, Lourenço and Branco (2013) provide evidence that the performance of sustainability related companies is larger in terms of return on equity when assessed in relation with a comparable set of financial assets. In fact, the importance of the assessment of the marginal impact of sustainability related financial assets on diversified portfolios increased to the level at which it was thoroughly theoretically developed in Dorfleitner and Utz (2012) that developed a methodological framework for the portfolio management analysis with probabilistic constraints. Albu et al. (2015a) and Albu et al. (2015b) study the relation between the asymmetry found in the dynamics of volatilities and the evolution of macroeconomic variables, sentiment indicators included. In a related field, fed by various previous analyses of the behavior of the dynamics of financial assets after the inclusion in an important stock market index, a set of papers discuss the effect of the inclusion of a company in a sustainability related stock market index. For instance Ziegler and Schröder (2010) analyzed this impact for the two most important Dow Jones Sustainability Indices and cannot provide sufficient evidence in the support of increased performance. In the same vein Oberndorfer et al. (2013) studied the inclusion of German corporations in the same indices and showed that actually stock markets may penalize these companies, while Cheung and Roca (2013) performed a similar investigation for the Asia Pacific markets and found the same reduction in performance.

Our paper provides an analysis of the differences between the risks associated with the regular benchmark equity indices and the sustainability related equity indices. We study the dynamics of these risks at daily and intraday frequencies and discuss their power to explain sentiment indices on macroeconomic conditions. In order to achieve these objectives we are using many volatility models for the estimation of the historical dynamics of risk as well as a volatility index, computed as an average of all the models in our analysis. In depth presentation of these models will be realized in the following section. The characterization of these trends in volatilities is realized by comparing their dynamics for the sustainability indices with the dynamics of the regular capital market indices, used as benchmarks for the global market. A set of MIDAS regressions will be performed in the end in order to investigate the relationship with the sentiment indicators.

The paper continues with a presentation of the data and the dynamics of the stock market indices to be computed, then we show the methodological issues that were taken into account for our analysis and a discussion of our results. The paper ends with some concluding remarks.

2. Data and Methodology

Data was provided by Reuters-Datastream with a daily frequency and by the Bloomberg platform for the intra-day frequency and consists in a set of benchmark equity indices for the US and European markets at the daily frequency and world and European indices for the intra-day analysis. The set of equity indices that are related to sustainability issues consists of the following financial assets:

- sustainability related equity indices activating in the European markets, with daily frequency: Euro Stoxx Sustainability; Euro Stoxx Sustainability less Alcohol, Tabaco, Gambling, Firearms and Armaments; Dow Jones Stoxx Sustainability; Dow Jones Stoxx Sustainability less Alcohol, Tabaco, Gambling, Firearms and Armaments; Euro Stoxx Sustainability 40; Stoxx EURO Sustainabiliy less Alcohol, Tabaco, Gambling, Firearms and Armaments;
- sustainability related equity indices activating in the US markets, with daily frequency: Dow Jones Sustainability Emerging Markets; Dow Jones Sustainability US Markets; Dow Jones Sustainability Index excluding alcohol; Dow Jones Sustainability Index excluding Armament; Dow Jones Sustainability Index excluding Tobacco; Dow Jones Sustainability Index excluding all; Dow Jones Sustainabiliy Index excluding Alcohol, Tabaco, Gambling, Firearms and Armaments;
- benchmark indices for the European markets, with daily frequency: Stoxx Europe 600; Stoxx Europe; Stoxx Europe 600 Banks; Stoxx Europe 600 Insurance; Stoxx Europe 600 Auto & Parts; Stoxx Europe Construction and Materials; Stoxx Europe Food and Beverages; Stoxx Europe Healthcare; Stoxx Europe Oil and Gas;
- benchmark indices for the US markets, with daily frequency: S&P 500 Industrials; S&P 500 Energy; S&P 500 Financials; S&P 500 Utilities; S&P 500 Banks 17 constituents; S&P 500 Consumer Discretionary; S&P 500 Healthcare; S&P 500 Materials; S&P 500 Automobiles; S&P 500 Banks 15 constituents; S&P 500 Composite;
- sustainability and benchmark equity indices, with intra-day frequency: Dow Jones Sustainability World Index; Dow Jones Sustainabiliy Europe Index; S&P 500 Composite Index; Europe Stoxx 600 Index.

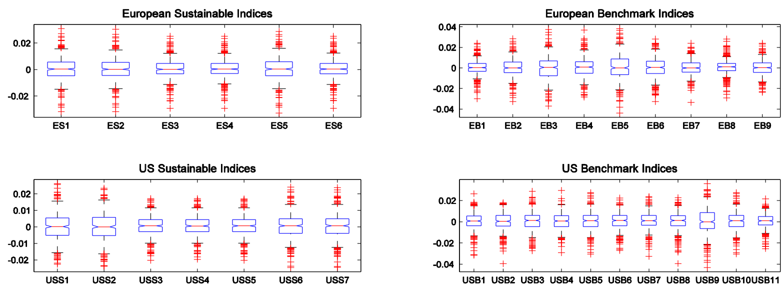


Figure 1. Statistical properties of all daily log-returns

We have chosen daily data for the common period starting from October 15, 2001 until August 22, 2014 for the European sustainability and composite indices, and from the February 21, 2013 until August 29, 2014 for the US sustainability indices. In Figure **Error! Reference source not found.** we show the statistical properties of each series of stock market indices' log-returns, at daily frequency.

One of the most important elements, which rooted our approach, is the fact that the dynamics of the sustainability related stock market indices show wider changes than the log-returns for the standard benchmark indices, which could be translated in larger risk. This phenomenon is a first proof that, at the daily basis, investor usually price the sustainability related indices as being safer investment instruments. Each plot exhibits the main statistical measure for the daily dynamics of log-returns computed for each stock market index in the period February 22nd, 2013 until August 29th 2014. We notice the fact that the returns for the sustainability equity indices have smaller standard deviations than the regular stock market indices, i.e. the benchmarks, both for the European and the US markets – log-returns for sustainability-related indices are presented in a scale from -0.02 to 0.02 both for US and European cases, while the benchmarks are presented in scales between -0.04 to 0.02 for US, and -0.04 and 0.04 for the European case.

The same situation can be observed in the case of the intra-daily series of log-returns for both of the categories of stock market indices. This time we take into account an equity index and a sustainability index for the European market and the respective pair for the global market. Figure **Error! Reference source not found.** exhibits the results for same-time returns dynamics at the five-minute frequency. In this case we used data that cover about 140 days, extracted from the Bloomberg platform. The larger spread of log-returns around their mean show that investors are consistent in attributing the same view on risk to the two types of stock market indices as in the daily cases.

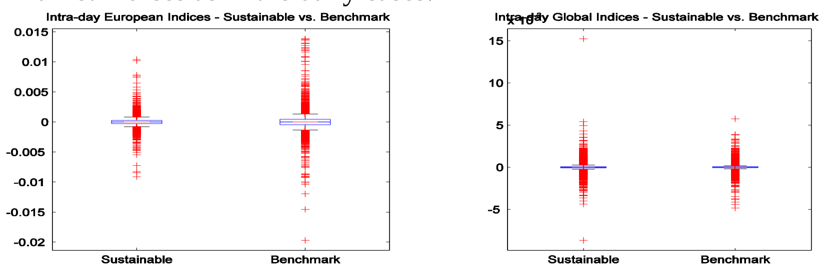


Figure 2. Statistical properties of intra-day log-returns

The plots show the statistical properties for the whole series of log-returns for the period covering March 3rd, 14:35 until September 9th, 20:10 in the case of the Global equity market and March 3rd, 8:05 until September 10th, 11:05 for the European stock market, with five-minute frequency. For both markets and for the two series of sustainable and benchmark indices, we extracted the common moments when they were traded such that we obtained consistent, same-time log-returns. We notice the wider spread of data in the case of the benchmarks as opposed to the sustainability indices in both markets. The main methodological tools employed in this paper consist in the use of a group of eight volatility models from the GARCH family as well as a volatility index computed as a weighted average of these models by taking into account their estimated likelihood as a measure of the in-sample performance.

2.1 Volatility models

We present here the models used for the computation of the volatilities for the two classes of equity indices. We employed a battery of models that accommodate a large set of statistical properties widely acknowledged by the literature (for instance Cont, 2001).

We are using a group of eight volatility models that are considered standard in the volatility literature. The first specification is the seminal GARCH model initially developed by Bollerslev (1986), with the following specification:

$$\begin{aligned} R_t &= \mu_t + \epsilon_t \\ \sigma_t^2 &= \omega + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 \epsilon_{t-2}^2 + \cdots + \alpha_p \epsilon_{t-p}^2 \\ \epsilon_t &= \sigma_t e_t \\ e_t &\sim N(0,1) \end{aligned} \tag{1}$$

The next volatility model is the EGARCH model, under the specification produced by Nelson (1991), which was developed with the objective to capture the asymmetric reaction of volatility in the case of the negative log-returns with respect to the positive ones. The standard specification is the following:

$$\begin{aligned} R_t &= \mu_t + \epsilon_t \\ ln(\sigma_t^2) &= \omega + \sum_{p=1}^{P} \alpha_p \left(\left| \frac{\epsilon_{t-p}}{\sigma_{t-p}} \right| - \sqrt{\frac{2}{\pi}} \right) + \sum_{0=1}^{O} \gamma_o \frac{\epsilon_{t-o}}{\sigma_{t-o}} + \sum_{q=1}^{Q} \beta_q ln(\sigma_{t-q}^2) \\ \epsilon_t &= \sigma_t e_t \\ e_t &\sim N(0,1) \end{aligned} \tag{2}$$

The same phenomenon of asymmetric reaction of volatility with respect to the sign of log-returns, also known under the name of leverage effect is captured by the GJR-GARCH developed by Glosten et al. (1993) and uses the following standard specification:

$$\begin{aligned} R_t &= \mu_t + \epsilon_t \\ \sigma_t^2 &= \omega + \sum_{p=1}^{P} \alpha_p \epsilon_{t-p}^2 + \sum_{o=1}^{O} \gamma_o \epsilon_{t-o}^2 I_{[\epsilon_{t-o}<0]} + \sum_{q=1}^{Q} \beta_q \sigma_{t-q}^2 \\ \epsilon_t &= \sigma_t e_t \\ e_t &\sim N(0,1) \end{aligned} \tag{3}$$

The so-called APARCH model uses an extension of the GJR-GARCH model with the objective to model the same leverage effect using more parameters.

This model was developed by Ding, Granger, and Engle (1993) under the following specification:

$$R_t = \mu_t + \epsilon_t$$

$$\sigma_t^{\delta} = \omega + \sum_{j=1}^{max(P,O)} \alpha_j\left(|\epsilon_{t-j}| + \gamma_j \epsilon_{t-j}\right)^{\delta} + \sum_{q=1}^{Q} \beta_q \sigma_{t-q}^{\delta} \qquad (4)$$

$$\epsilon_t = \sigma_t e_t$$

$$e_t \sim N(0,1)$$

With similar objectives and also rather improved performance with respect to the simple GARCH model, Zakoian (1994) developed the so-called ZARCH (from the name of the author) or TGARCH (Threshold GARCH) model with the specification:

$$R_t = \mu_t + \epsilon_t$$

$$\sigma_t = \omega + \sum_{p=1}^{P} \alpha_p |\epsilon_{t-p}| + \sum_{o=1}^{O} \gamma_o |\epsilon_{t-o}| I_{[\epsilon_{t-o}<0]} + \sum_{q=1}^{Q} \beta_q \sigma_{t-q} \qquad (5)$$

$$\epsilon_t = \sigma_t e_t$$

$$e_t \sim N(0,1)$$

Using a non-linear dependence of the standard deviation on the sign of shocks in the dynamics of stock market returns, Ding, Granger, and Engle (1993) created the NAGARCH or NGARCH (non-linear GARCH) model with the specification:

$$R_t = \mu_t + \epsilon_t$$

$$\sigma_t = \omega + \sum_{p=1}^{P} \alpha_p \left(\epsilon_{t-p} - \gamma\sqrt{\sigma_{t-p}}\right)^2 + \sum_{q=1}^{Q} \beta_q \sigma_{t-q} \qquad (6)$$

$$\epsilon_t = \sigma_t e_t$$

$$e_t \sim N(0,1)$$

The important feature of long persistence of volatilities is captured by the IGARCH (Integrated GARCH) model, according to a specification developed by Engle and Bollerslev (1986):

$$R_t = \mu_t + \epsilon_t$$

$$\sigma_t^2 = \omega + \sum_{p=1}^{P} \alpha_p (\epsilon_{t-p})^2 + \sum_{q=1}^{Q} \beta_q \sigma_{t-q}^2 \qquad (7)$$

$$\epsilon_t = \sigma_t e_t$$

$$e_t \sim N(0,1)$$

The same phenomenon of large persistence is obtained using the more recent FIGARCH (Fractionally Integrated GARCH) model, developed by Baillie, Bollerslev, and Mikkelsen (1996):

$$R_t = \mu_t + \epsilon_t$$

$$\sigma_t^2 = \omega + \left(1 - \beta L - \phi L(1-L)^d\right)\epsilon_t^2 + \beta \sigma_{t-1}^2 \qquad (8)$$

in which L is estimated by a model with the specification $\sigma_t^2 = \omega + \sum(\lambda_i \epsilon_{t-1}^2)$ and λ_i is a function of parameters ϕ and β. As in the previously mentioned volatility models, we mention the standard approach $\epsilon_t = \sigma_t e_t$, $e_t \sim N(0,1)$.

Each model was fitted with errors following the normal, Student-T, GED and a skewed distribution1, which means that we performed four estimations for each model and each equity index, both at the daily and the intra-day frequency, accordingly. As far as the intra-daily equity indices are concerned, previous research proved the existence of patterns in the absolute values of log-returns, therefore a GARCH-type of model for these series of returns is not suited unless adjusted for periodicities. We follow the methodology of Boudt et al. (2011a) and Boudt et al. (2011b) in order to compute the periodicity of each intra-day series of log-returns and to use it in order to provide the proper adjustment for the estimation of the volatility models. Therefore, each of the models presented above were used for the estimation of volatilities for the intra-day equity indices on the five-minute log-returns adjusted with periodicity statistics.

2.2 A Volatility index

In order to enhance our volatility analysis we also decided to develop a model that covers the dynamics captured by the previously presented models of volatility, by means of likelihood performance, i.e. an in-sample analysis of the previously fitted volatility models.

As previously mentioned, each model was estimated with four types of errors (following a normal, Student-T, GED and a skewed distribution). Our weighting procedure for the development of the volatility index consists in the use of the likelihoods estimated for each type of models across each of the four possible errors in a two-stage process. We first computed the sum of the likelihoods for the four types of errors estimated for each specification. Each combination of model specification and error type received a weight based on the percentage the corresponding likelihood has with respect to the sum of all likelihoods for the same model. The volatility index will take into account the sum of all the weights computed for each model and will allocate to each model a weight corresponding to the percentage the likelihood has out of the sum of all likelihoods.

These likelihoods were used for the computation of the weights used in the estimation of the composite volatility index for each financial asset.

[1] The estimation of all these models was performed by using the MFE toolbox developed by Kevin Sheppard.

Table 1. Statistical properties of Sentiment Indices

Sentix Europe	Mean	Standard Deviation	Median	ADF p-value Raw	ADF p-value First Difference
CURRENT SITUATION-INSTITUTIONAL	20.52113	32.28611	28.5	0.268507	0.001
CURRENT SITUATION - PRIVATE	21.25	30.18106	27	0.307773	0.001
FUTURE EXPECTATION-INSTITUTIONAL	8.911972	18.38172	10	0.021672	0.001
FUTURE EXPECTATION - PRIVATE	11.16197	17.53695	10.25	0.103098	0.001
INVESTORS SENTIMENT	15.01092	21.98859	16.07	0.195551	0.001
CURRENT SITUATION	20.88556	31.15862	27.875	0.307687	0.001
FUTURE EXPECTATION	10.03697	17.57797	9	0.058614	0.001
ZEW Europe					
GENERAL	25.05561	37.18074	29.5	0.122021	0.001
HIGHER	40.1861	23.13871	37.4	0.337306	0.001
LOWER	15.13048	16.30487	9.2	0.101161	0.001
SAME	44.68342	14.83545	47.1	0.262318	0.001
EUROZONE	25.05561	37.18074	29.5	0.122021	0.001
Sentix US					
CURRENT SITUATION-INSTITUTIONAL	5.69	32.70537	9.75	0.183218	0.001
FUTURE EXPECTATION-INSTITUTIONAL	-0.8662	18.09284	1.75	0.006806	0.001
CURRENT SITUATION - PRIVATE	4.133803	27.01221	9	0.160015	0.001
FUTURE EXPECTATION - PRIVATE	-1.01761	14.21534	0.25	0.004652	0.001
CURRENT SITUATION	4.911901	29.78221	9.75	0.197499	0.001
FUTURE EXPECTATION	-0.9419	15.88519	1.375	0.008259	0.001
INVESTORS SENTIMENT	1.490423	19.90855	5.485	0.073264	0.001
ZEW US					
GENERAL	10.38787	36.83825	4.05	0.023063	0.001
HIGHER	29.65331	23.69123	23.6	0.148653	0.001
LOWER	19.26544	16.87484	14.2	0.05618	0.001
SAME	51.08125	18.30335	47.9	0.376189	0.001

Due to the different frequencies, the connection between the two groups of time series is investigated using the so-called2 ADL-MIDAS (p_Y^Q ,) in keeping with the specifications in **Error! Reference source not found.** (2013):

$$Y_{T+1}^{Q} = \mu + \sum_{j=0}^{p_Y^Q - 1} \alpha_{j+1} Y_{t-j}^{Q} + \beta \sum_{j=0}^{q_X^D - 1} \sum_{i=0}^{N_D - 1} w_{i+j*N_D}(\theta^D) X_{N_D - i, t-j} + u_{t+1} \quad (9$$

where the weighting configuration, $w(\theta^D)$, is constructed by using an Almon lag polynomial as follows:

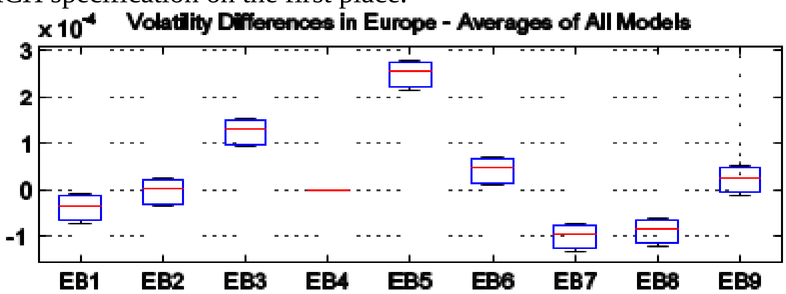
[2] Mi(xed) Da(ta) S(ampling).

$$w_j(\theta^D) = w_j(\theta_1, \theta_2) = \left(\exp \theta_1 j + \theta_2 j^2\right) / \left(\sum_{j=1}^{m} \exp(\theta_1 j + \theta_2 j^2)\right) \qquad (10)$$

This methodological development allows the connection of a low-frequency dependent variable (denoted by Y_t^Q in equation 9), which in our case will be represented by the monthly sentiment indicators with a high-frequency variable (denoted by X_t^D in the same equation 9), represented by the daily differences in the estimated variances for each of the eight volatility models and the proposed volatility model.

3. Results and discussions

The set of eight models from the GARCH family were estimated for the each series of the stock market indices mentioned in the previous section. We can notice that the models with the highest performance (and accordingly are included in the volatility index with a larger weight) are usually the NAGARCH model, followed by the APARCH model and the EGARCH model. All of these models include specifications that cover the leverage effect, as one of the factors that produce high kurtosis, besides the time varying volatilities allowed by all the GARCH models. There is not a very high persistence in the volatilities for these models, as could be captured by the IGARCH and FIGARCH specifications, since they tend to have a smaller estimating power (slightly better in the case of the FIGARCH model), while the rest of the models have an in-between performance. The model with the smallest likelihood is the simple standard GARCH model. However, looking at the likelihood values for each asset we can notice that models' performances are not highly spread, i.e. they exhibit a very low standard deviation, suggesting that the models are producing very similar results. However, even inside these small variations, we notice that the ranks are quite stationary, keeping the NAGARCH specification on the first place.



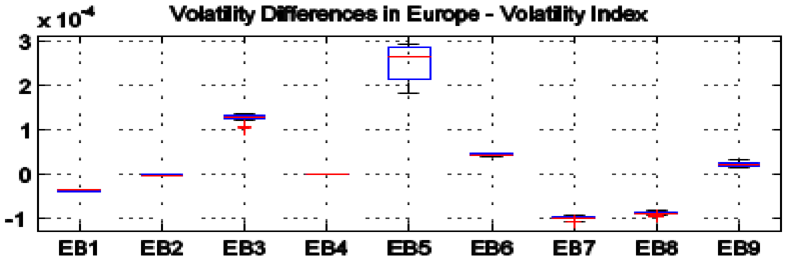


Figure 3. Statistical properties of Differences in Variances at the Daily Frequency for European Markets

The plots show the statistical properties of the differences in variances for the whole series of log-returns with daily frequency for the European stock markets. In the upper part, each boxplot contains a set of averages in the variances computed using the eight volatility models, for each possible difference between each benchmark index (EB in the abscise axis) and each of the six sustainability indices (described in Section 2). The lower part shows the same differences only for the case of the volatility index presented in Section 2.2. The plots in Figures 3 and 4 show two the statistical properties of for the average differences in the variances of the log-returns computed between the benchmark capital indices and the sustainability-related capital indices using two modeling approaches.

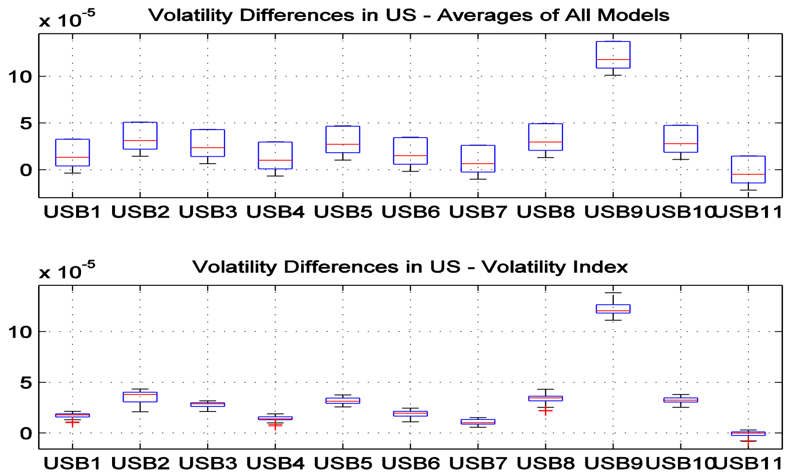


Figure 4. Statistical properties of Differences in Variances at the Daily Frequency for US Markets

On the upper charts we exhibit the averages of the differences in these variances computed using all of the eight volatility models; the time series presented here show the simple averages across these models. Each box in these charts shows the statistical properties of the averages of the distances between the European benchmark index (EBx in the abscise axis) and each of the European sustainability index (six indices for European markets), in the upper part of Figure 3 and corresponding US benchmark indices less their respective sustainability indices (each of the seven indices presented in the Section 2), in the upper chart of Figure 4. The lower part of these two charts shows the results for the two markets (European in Figure 3 and respectively US market in Figure 4) of the volatility index presented in Section 2.2. We can notice the smaller size of the boxes for this set of time series, which proves the fact that our composite model succeeds to provide more efficient estimates of the differences, i.e. the distances are less volatile when compared with the averages across all the volatility models.

A positive value on the chart shows larger volatilities for the benchmarks as opposed to the sustainability indices, which is almost consistently the case for the US markets and almost holds for the European markets. The negative distances are present for the case of the Stoxx Europe Food and Beverages index and Stoxx Europe Healthcare index, which show that investors perceive these two industries as less risky, i.e. with levels of risks that are event better than the sustainability indices. This is due to the fact that these two industries are part of the sustainability field by their nature. These positive values of the differences in variances prove our expectation that the benchmarks are more volatile, i.e. riskier than the sustainability indices in general. The large set of volatility models as well as the use of the composite volatility model (the volatility index) proved this for all the distances computed between the two classes of indices presented in Section 2.

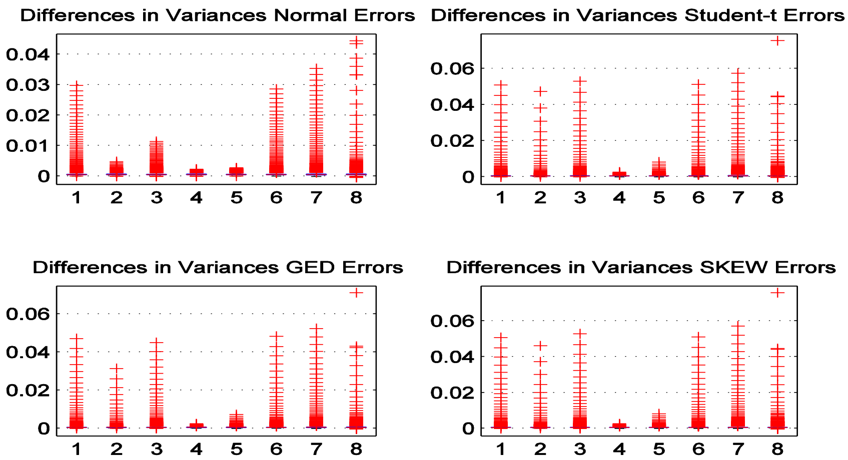


Figure 5. Statistical properties of Differences in Variances for European Indices at Intra-day frequency

At the intra-day level we used the same set of models to compute the differences in variances. Figure 5 shows the statistical properties of these differences for each of the eight types of models and for each type of errors used in their calibration. We can notice the fact that the vast majority of these values are positive, their distribution is positively skewed. The plots show the statistical properties for the differences in variances for the whole series of log-returns with intra-day five-minute frequency in the case of the European stock markets using the eight volatility models described in the subsection 2.1, with four types of errors: normal, student-t, GED and skewed errors.

In Figure 6 the same statistical properties are exhibited for the differences in variances computed through seven volatility models for the Global indices at the five-minute frequency. We notice that these values have the tendency to be smaller than in the case of the European differences, but they still feature the large proportion of positive values, which prove the tendency of benchmark equity indices to be more risky than their sustainability counterparts at the global level too, i.e. for well diversified portfolios.

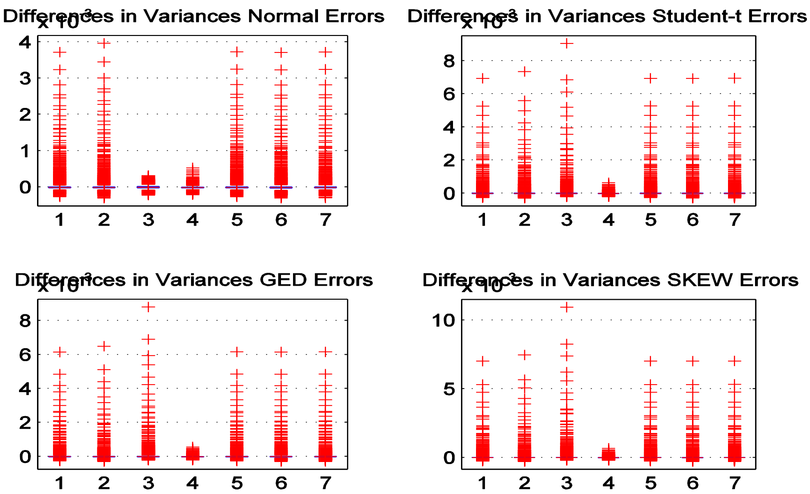


Figure 6. Statistical properties of Differences in Variances for Global Indices at Intra-day frequency

The plots show the statistical properties for the differences in variances for the whole series of log-returns with intra-day five-minute frequency in the case of the global stock markets using the eight volatility models described in the subsection 2.1, with four types of errors: normal, student-t, GED and skewed errors.

In order to understand the connections among the different financial assets that reflect sustainability related trading strategies, the volatilities estimated for each asset using each model were compared between the two classes of assets - those that cover only sustainable equity instruments on one hand and the usual benchmarks for the global equity markets altogether, on the other hand. We show here the results of these series of comparisons, for different classes of assets and for different periods, where applicable.

The found differences in the dynamics of volatilities for the two groups of stock market returns stimulate the necessity to understand their causes. One direction of reasoning could be the fact that the sustainability indices could proxy that part of economy that people consider to be most resilient, i.e. the economic activities with the highest probability to last and survive the possible systemic shocks to be realized in the future. From this perspective, the difference in volatilities could represent an asset pricing factor, one that should be related with people's expectations about the future dynamics of business conditions. To account for this possible phenomenon we are using sentiment indicators (Sentix and ZEW) to analyze whether the differences in volatilities could explain these forecasts, could be considered as a possible factor for the future trends. The connections between the differences in volatilities with a daily frequency and the changes in the sentiment indicators (as log-returns) were performed using the MIDAS methodology in order to treat the problem of different frequencies.

We present the results in the Tables 2 and 3, which cover the synthesis of the MIDAS regressions performed for all the pairs of two variables, one belonging to the group of differences in the variances (with a daily frequency) as explanatory variables and the other one belonging to the group of sentiment indices. This resulted in a battery of regressions equal to 32 models (eight models with four types of errors) times 7 Sentix indicators for the European markets in the first part of Table 2 and 32 models times 7 Sentix indicators for the US markets in the second part of the same table. Under the same logic, we ran a number of MIDAS regressions equal to 32 models times 5 ZEW indicators in the upper part of Table 3 and another 32 models times, 4 indicators regressions in the lower part of the same table. Therefore, the two tables provide two types of information: on one hand we have in the first four columns information about the average statistics resulted from the regressions and on the other hand, the last four columns cumulate the information about the t-statistics for regressions that were performed across each type of errors (equal to eight regressions for each type).

The first important element to notice here is the fact that the t-statistics are quite large for the connections that we intended to develop in this analysis. The most important statistically significant values are observed for the Sentix indicators that reflect the Current situation, both private and institutional, in the case of the European market coverage and for the institutional future expectations (mostly institutional) for the US markets. The most important result is the fact that the general Investors' Sentiment indicator exhibits statistical significance for both markets. We notice that, when looking deeper in the structure of the series of regressions' results, these significant values are consistent for each class of errors, and they have a small standard deviation, which proves the fact that the MIDAS dependence is strong in the case of the Sentix indicators. The sign of the parameters is consistently negative in all the situations, which drives us to conclude that a large difference between the risks associated to general economic activities (represented by the dynamics of benchmark equity indices) and the risks for the sustainability related equity indices corresponds to a reduction in the Sentix values for the respective indicators.

Looking at the ZEW results in Table 3, we notice the fact that the t-statistics are important especially in the case of the General, Eurozone and Lower indicators for the European markets. As in the case of the Sentix indicators, we notice that the t-statistics have the same large values (they show statistical significance) for each type of models, when we divided them into models fitted with the four types of errors. We can also see that for the US market, there is not clear statistical significance of the relation between the differences in risks and the dynamics of the ZEW indicators. The sign of the significant dependences show however that a large risk difference induces a larger value for the general sentiment indicator, which is contrarian to the results provided for the case of the Sentix indicators.

The table exhibits the results of the MIDAS regressions for all the pairs of two variables, one from the group of differences in the variances (with a daily frequency) as explanatory variables and the other one belonging to the group of sentiment indices. There are regressions resulted from 32 models (eight models with four types of errors) times 7 Sentix indicators for the European markets in the first part and 32 models times 7 Sentix indicators for the US markets in the second part.

Table 2. Results of MIDAS regressions with Sentix Sentiment Indices as Independent Variables

	Average Regression Statistics				T-stats each type of Volatility Model			
	Average Paramet. values	Average T-stats	StDev of T-stats	Average Goodness of Fit	Normal Errors	T-distrib Errors	GED Errors	SKEW Errors
Results for the European Market								
Current sit. institutional	-24713.2	-4.72052	1.026619	0.189668	-5.04864	-4.338	-4.69084	-4.687
Current sit. - private	-24697.4	-4.93694	1.446652	0.263571	-4.9342	-5.40679	-4.8529	-4.67133
Future expect.-institutional	-4818.03	-1.18145	0.629057	0.048514	-1.0409	-1.0668	-1.14422	-1.54556
Future expect. - private	-2753.75	-1.21369	0.372498	0.011725	-1.13074	-1.34463	-1.18279	-1.22978
Investors sentiment	-14352.3	-3.41833	0.727612	0.099403	-3.43043	-3.48657	-3.71518	-3.08927
Current situation	-23694.1	-4.95786	1.491543	0.264399	-4.70333	-5.09233	-5.1813	-4.82244
Future expectation	-3284.12	-1.30005	0.550823	0.018966	-1.32416	-1.14057	-1.39721	-1.26205
Results for the US Market								
Current sit. - institutional	-51876.8	-1.46904	0.306667	0.137655	-1.39779	-1.4691	-1.41377	-1.5866
Future expect.-institutional	-76953.9	-2.61257	0.673194	0.218531	-2.41494	-2.84877	-2.35707	-2.86901
Current situation - private	-61425.5	-1.78116	0.610907	0.171047	-1.78836	-1.69851	-1.82804	-1.80029
Future expect. - private	-47440.7	-1.76463	0.339244	0.157499	-1.93831	-1.7576	-1.82876	-1.59162
Current situation	-58299.9	-1.78427	0.480192	0.183836	-1.76493	-1.77174	-1.69698	-1.92862
Future expectation	-61924	-2.37036	0.755116	0.212385	-2.51655	-2.19275	-2.51149	-2.27634
Investors sentiment	-58730.8	-2.28812	0.799414	0.232203	-2.54061	-2.24873	-2.12971	-2.25985

The Table 3 exhibits the results of the MIDAS regressions for all the pairs of two variables, one from the group of differences in the variances (with a daily frequency) as explanatory variables and the other one belonging to the group of sentiment indices. There are regressions resulted from 32 models (eight models with four types of errors) times 5 ZEW indicators in the first part and 32 models times 4 indicators in the second part.

Table 3. Results of MIDAS regressions with ZEW Sentiment Indices as Independent Variables

	Average Regression Statistics				T-stats each type of Volatility Model			
	Average Parameters values	Average T-stats	StDev of T-stats	Average Goodness of Fit	Normal Errors	T-distrib Errors	GED Errors	SKEW Errors
Results for the European Market								
GENERAL	19176.79	2.905394	0.321402	0.231583	2.899262	2.900987	2.799126	3.005512
HIGHER	5175.444	1.183521	0.315591	0.207021	1.106572	1.264543	1.194739	1.160443
LOWER	-13160.4	-3.50455	0.407544	0.152246	-3.46628	-3.5331	-3.46604	-3.55758
SAME	6872.359	1.498695	0.422006	0.056844	1.436976	1.661649	1.381769	1.770441
EUROZONE	19176.79	2.905394	0.321402	0.231583	2.899262	2.900987	2.799126	3.005512
Results for the US Market								
GENERAL	64493.68	0.966148	0.277492	0.056319	0.963005	0.954492	0.983359	0.964039
HIGHER	44597.3	0.741678	0.344623	0.051964	0.649248	0.771524	0.692995	0.828521
LOWER	-2541.43	-0.33989	0.33772	0.040146	-0.35664	-0.40062	-0.26613	-0.42337
SAME	-28618.7	-0.53472	0.39973	0.103282	-0.43449	-0.55192	-0.55889	-0.60454

4. Conclusion

This papers investigates the dynamics of the sustainability equity indices with both daily and intra-daily frequency in order to establish the existence of a statistically significant difference between the risks entangled by investments in portfolios composed of this kind of assets and the risks associated to the regular stock market indices, considered as benchmark portfolios for international investors. Using a large set of volatility models that cover thirty two specifications from the GARCH family and an ad-hoc volatility index developed based on the in-sample performances of these models we prove that these differences exist at both frequencies. The estimation results helped in the identification of the best volatility models for each class of equity indices.

A discussion about the economic intuition of this difference is provided by the fact that sustainability related equity indices correspond to long-term economic activities, usually perceived as sound investments for long horizons, with clientele like pension funds and insurance funds. In this respect these differences may be considered as a pricing factor under the theoretical framework of Arbitrage Pricing Theory. The analysis could be extended by an analysis of the persistence of these differences.

Given the fact that they could represent a significant element in the analysis of long-term investing, we also test the extent to which they are able to explain the usual market consensus about the future economic dynamics. In order to investigate this assertion we are using a large set of Sentix and ZEW sentiment indicators for the European and US markets. Their monthly frequency required the use of a special methodology that could allow for the study of the dependence between risk differences (available at the daily frequency) and the corresponding sentiment index, We are using the ADL-MIDAS toolbox in order to construct this analysis and we build a large set of measures for the linear dependences via different frequencies for all the thirty two model specifications and for each sentiment indicator in the two regional markets.

Our results show statistical significance of the dependence between risk differences and the Sentix indicators both in Europe and in US. However, we did not obtain the same results in the case of the ZEW indicators, which require further investigation.

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