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Do ESG Factors Prove Significant Predictors of Systematic and Downside Risks in the Russian Market after Controlling for Stock Liquidity?

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Abstract: This paper reveals the impact of environmental, social, and governance (ESG) scores on systematic and downside risks in the Russian stock market. We analyze the influence of a broad set of ESG factors controlling for stock liquidity, financial indicators of companies, and macroeconomic indicators. The period under consideration is from 2013 to 2021. The methodology of our research is based on regression analysis with multiplicative variables to reveal the changes induced by the COVID-19 pandemic. We obtain several novel results. Social responsibility is one of the most significant non-fundamental factors influencing both systematic and downside risks. The most important environment-related component is the measure of a company's propensity to environmental innovations. Some dimensions of stock liquidity are also significant. For some factors, such as the COVID-19 pandemic and debt burden, we find an unexpected direction of influence on liquidity.

Keywords: ESG; downside risk; systematic risk; panel data; COVID-19

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1. Introduction

Over the past few decades, investors, asset managers, and researchers have become increasingly more aware of sustainable business development. This concept suggests that a company's policy should take into account the effects on society, environment, and corporate governance, i.e., ESG practices (Bele et al. 2023).

The COVID-19 pandemic showed the necessity of protecting the interests of all stakeholder groups. Jin and Lei (2023), for the Chinese market, showed that higher aggregate and individual ESG scores can increase corporate value and the level of innovation. The growth of ESG investment has led to growing interest in the drivers of systematic and downside risk from ESG investment. While the impact of ESG scores on financial performance is well investigated (Bax et al. 2023), risk determinants have been studied to a lesser extent.

Our objective is to analyze the impact of indicators of environmental protection, social responsibility, and corporate governance on systematic and downside risk controlling for liquidity measures. In this analysis, we focus on the emerging Russian stock market, which is characterized by low liquidity.

Kahneman and Tversky (1979) and Tversky and Kahneman (1987) developed prospect theory explaining people's risky decision making. One of its key ideas is the loss aversion bias, i.e., a greater sensitivity to losses than to potential gains (Liu 2023). Several studies have shown that loss aversion is an important driver of investment decisions (van Dolder and Vandenbroucke 2023; Gisbert-Pérez et al. 2022). The behavior of both private investors and financial professionals could be explained by this bias (van Dolder and Vandenbroucke 2023).

While the systematic risk measure (beta coefficient) is based on the symmetrical likelihood of a loss or gain, downside risk measures (for example, value at risk or downside beta) focus on the risk of an investment loss, which becomes sizable during financial crises such as the COVID-19 pandemic. Estrada (2006), following Harry Markowitz, viewed downside risk as a better way to assess risk than the "mean-variance" framework and claimed that downside approach is often preferable to the traditional asset price models. Empirical research shows that stock returns are not normally distributed and are characterized by skewness (Hoepner et al. 2023). Bax et al. (2023) claimed that the understanding of the manifestation of tail risk is important for asset pricing and risk management. According to Liu (2023), downside beta plays a crucial role in asset pricing. Solving the task of portfolio selection based on Markovitz optimization techniques, Kumar et al. (2022) note the asymmetry of risk and underscore the importance of semi-variance analysis. The authors find that the market portfolio derived from the semi-variance approach has a relatively lower risk and higher (adjusted) Sharpe ratios than the portfolio derived from the mean-variance approach.

Recent major shocks in financial markets, caused by the COVID-19 pandemic and rising geopolitical tensions in the world, make it urgent to study the determinants of downside risk. Chaudhary et al. (2020) focus on the influence of the COVID-19 pandemic on the largest 10 countries by GDP and reveal daily negative mean returns for all market indices during the beginning of the COVID period. The authors highlight a devastating impact of the crisis on economies and stock markets and find that the COVID variable is significant and positive for stock volatility. Hung et al. (2021) state that many investors are concerned about downward trends in the stock market and choose "safe-haven assets" to mitigate risks during financial turmoil. The authors show that the number of daily COVID-19 confirmed cases in Vietnam has a negative impact on stock returns. Therefore, systematic and especially downside risks are of great importance for institutional investors, including pension funds (Ang et al. 2013), banks, and insurance companies due to regulatory requirements (Hoepner et al. 2023).

The theoretical framework of our paper is as follows. According to stakeholder theory, stakeholders support firms in making decisions and achieving business goals, thereby contributing to the success of their business (Freeman 2006). By implementing ESG strategies and publishing ESG reports, firms should cater to the needs of different groups of stakeholders. For example, investors are interested in whether firm activities comply with national laws and rules (Jin and Lei 2023).

According to signaling theory, investors should thoroughly analyze ESG reports provided by firms to mitigate the risks of information asymmetry (Jin and Lei 2023). Anita et al. (2023) and Qiu et al. (2016) find that a company's adherence to ESG practices generates positive signals for investors and improves the company's competitiveness. Therefore, we can assume that better ESG indicators lower systematic and downside risks (Albuquerque et al. 2019).

On the other hand, ESG measures can be costly for firms. The European Banking Authority (EBA) concludes that ESG factors may result in the growth of "credit, market, operational, liquidity, and funding risks".[1] Teplova et al. (2023) reveal that some measures of environmental protection in the Russian market tend to decrease stock liquidity. This may lead to an increase in systematic and downside risks. Thus, the results of previous studies are mixed, and the direction and significance of ESG scores for systematic and downside risks is an open research question.

Our motivations to study the role of ESG for risk in the Russian stock market are as follows. It is a large emerging market characterized by a high share of minerals extraction in GDP, export-oriented economics, slow economic growth (the average annual real GDP growth in 2013–2023 was 1.2%), high inflation in recent years, and several serious environmental problems such as the "depletion of natural resources, air and water pollution, large amount of household waste" (Teplova et al. 2023). Therefore, environmental and social responsibility issues and the quality of corporate governance are essential for studying risk determinants. The number of stock issuers in the MOEX index ranged from 38 to 50 during the period under consideration (2013–2021). MOEX tracks the performance of the largest Russian companies with stocks traded on the Moscow Exchange. The index represents ten sectors of the Russian economy, including oil and gas, metals, and industrial production. According to Statista, the ratio of Russia's market capitalization of domestic companies to GDP grew from 33.6% in 2013 to 45.8% in 2021 and sharply declined to 23.7% in 2022.[2] One of the major problems is the low liquidity of stocks. We take into account different liquidity measures because they are crucial in the Russian stock market.

Our contribution to the literature is three-fold. First, we consider the Russian market and identify the determinants of systematic and downside risks. Asafo-Adjei et al. (2022) analyzed the interdependence of systematic risks in 20 emerging market economies and revealed that the systematic risk in the Russian market was only loosely linked to systematic risks in other regional markets, which could be useful for portfolio diversification and risk management. Therefore, retail and institutional investors should also take downside risk into consideration. Most previous research papers investigating the determinants of systematic and downside risks focus on developed markets (Ali et al. 2022) or Asian emerging markets (Bui et al. 2017; Zhang et al. 2023; He et al. 2023). The determinants of these two types of risk in the Russian market have not been studied in detail, and our research fills this gap.

Second, we focus on the impact of non-fundamental indicators (primarily environmental responsibility, social responsibility, and the quality of corporate governance, i.e., ESG) controlling for liquidity characteristics. Across the world, ESG fund assets reached nearly USD 3 trillion at the end of 2023 despite a challenging macroeconomic situation (source: Morningstar, 2 February 2024). Many research papers investigate the relationship between ESG indicators and a company's financial performance and stock returns (Aastvedt et al. 2021; Xie et al. 2019). The influence of ESG components separately on a company's systematic and downside risks has been studied to a lesser extent because previous papers analyze the impact of aggregate ESG scores (Bax et al. 2023; Zhang et al. 2023). Our research fills this gap.

Third, we analyze the influence of the COVID-19 pandemic and use regressions with multiplicative variables to reveal changes in the impact of ESG scores during the pandemic. COVID-19 led to the disruption of supply chains, social isolation, increasing panic, and the growth of the share of retail investors in domestic stock markets (Teplova et al. 2023).

We obtain some novel results on the impact of environmental and social responsibility indicators, as well as liquidity indicators, on a company's systematic and downside risk.

Section 2 provides a literature review. Section 3 describes the methods. It outlines the hypotheses, describes the variables used in our research, presents the methodology, and provides descriptive statistics on the data. Section 4 presents the empirical results and discussion. Section 5 concludes the paper.

2. Literature Review

The literature that analyzes factors viewed as the determinants of systematic and downside risks is vast. Most articles investigated developed markets (primarily the US and European stock markets). Among emerging markets, the authors predominantly concentrated on the Chinese stock market (He et al. 2023; Zhang et al. 2023). The impact of several financial and non-financial factors (including ESG scores) on the systematic and downside risks of Russian public companies has been analyzed to a lesser extent.

The previous studies focused on firm age (Chincarini et al. 2020; Liu et al. 2022), debt burden (Hamada 1972; Adhikari 2015), the size of companies (Franzoni 2006; Olibe et al. 2008), profitability (Saji 2018), market capitalization (Rowe and Kim 2010), and many other aspects of a firm's characteristics as potential drivers of systematic risk.

Empirical researchers considered similar measures by analyzing different sources of downside risk. The authors primarily concentrated on several macroeconomic indicators (Camilleri et al. 2019), trading characteristics (Zhang et al. 2023), and firms' dividend policies (Farooq et al. 2021).

A separate branch of the literature concentrates on the impact of different ESG factors on a company's systematic and downside risks. Martín-Cervantes and Valls Martínez (2023) use the random forests methodology to study the relationship between betas and various financial and non-financial variables on a sample of liquid US stocks. The authors reveal that ESG factors "constitute the main variable on the formation, determination, and sign of betas". Using a sample of Australian public companies, Ali et al. (2022) demonstrate that downside risk proxied by different value-at-risk metrics is negatively affected by board quality and corporate governance quality. Boubaker et al. (2020) reveal that corporate social responsibility reduced financial distress risk for US-listed firms from 1991 to 2012. Hoepner et al. (2023) show that public companies can reduce downside risk by adopting ESG practices.

The literature on the impact of ESG factors on a company's risks and risk management in emerging markets is rather scarce. Zhang et al. (2023) find that stocks of Chinese companies with high ESG scores have significantly lower downside risk measured by the lower partial moment and value at risk than their brown peers. He et al. (2023) also analyze the Chinese market (2010–2020) and find that the adoption of ESG standards significantly reduces corporate risk taking. There are three channels that include information transparency, corporate governance, and external monitoring pressure. Suttipun (2023) concentrates on a sample of Thai companies (2017–2021) and finds that ESG performance is negatively associated with corporate risk measured by the debt-to-equity ratio. This is explained by the fact that better ESG performance signals creditors that the company is well managed. Qian et al. (2023) find that better ESG performance in the Chinese market is associated with a bigger size of bank loans and a lower cost of bank loans in China. The authors suggest that larger social responsibility and better corporate government reduce risks and increase information transparency for creditors. Companies with high ESG scores also benefit from employee and customer loyalty, which increases their resilience to exogenous shocks and lowers downside risks.

Many recent empirical studies document lower volatility and higher returns for high-ESG stocks during the COVID-19 pandemic compared to their low-ESG peers (e.g., Albuquerque et al. 2020; Yu 2022). However, the conclusions on the impact of the COVID-19 crisis are mixed. Some authors note that during this crisis, downside risk significantly increased for green stocks (Lashkaripour 2023). Some other studies (e.g., Lööf et al. 2022) reveal that, during the COVID-19 financial meltdown, green stocks had lower financial risk. As for emerging markets, Broadstock et al. (2021) analyze the performance of high-ESG and low-ESG portfolios of Chinese stocks during the COVID-19 crisis and find that good ESG performance tends to mitigate financial risk. Gupta and Chaudhary (2023) compare the performance of ESG indices against broad market indices in emerging markets (India, Brazil, and China). By assessing one-year rolling returns, the authors show that ESG indices outperform the overall market indices and show positive alpha in China and India. ESG portfolios provide more downside risk protection and demonstrate a higher upside beta than downside beta in Brazil and China.

3. Methods

3.1. Research Hypotheses and Variables

For a sample of 36 liquid Russian stocks, we obtain the following yearly ESG scores from the Eikon Refinitiv database ranging from 0 (minimum) to 100 (maximum): aggregate ESG scores, social responsibility scores, corporate governance scores, environmental responsibility scores, resource use scores, emissions scores, policy emissions scores, environmental management team scores, environmental supply chain management scores, water withdrawal policy scores, and energy policy scores. The last three variables have been logarithmized to alleviate the issue of multicollinearity between different sustainability scores. The time frame of the collected ESG data is from 2013 to 2021, and the number of year–stock observations is 280. In addition, Thomson Reuters Refinitiv provided yearly data on net-debt-to-EBITDA ratios, ROAs, interest coverage ratios, ROEs, operating margin ratios, the ratios of market capitalization to net asset value (Tobin's Q), the logs of market capitalization and revenue, and the levels of revenue growth (%, year to year). Many authors (e.g., Teplova et al. 2023), who studied the relationships between ESG scores and different stock-specific risks, used similar sets of fundamental variables as control variables.

Based on trade-level data, we calculate the relative monthly bid–ask spread for each stock, averaged for each year; the logarithm of monthly stock turnover, averaged for each year; monthly trading volume adjusted and not-adjusted for free float, averaged for each year; monthly free float, averaged for each year; and the logarithm of 1 plus the monthly Hui Heubel measure, averaged for each year. In our research, we consider two stock-specific measures of systematic risk, daily beta and daily downside beta, calculated over a specific year t in the following way: $Beta_{it} = \frac{cov(r_{id}, r_{md})}{Var(r_{md})}|_{d \in t}$ and $Down\_beta_{it} = \frac{cov(r_{id}, r_{md} \mid r_{md}<0)}{Var(r_{md} \mid r_{md}<0)}|_{d \in t}$, where r_{id} is stock i close-to-close log-return over day d, and r_{md} is the MOEX Russia Index's close-to-close log-return over day d. The condition $\mid r_{md} < 0$ means that covariance and variance are calculated conditionally on the market daily log-return being negative; the condition $|_{d \in t}$ means that stock-specific measures of systematic risk over year t are calculated only over trading days d within year t.

The Russian stock market is rather illiquid and is characterized by frequent instances of market liquidity evaporation (e.g., Obizhaeva 2016). Teplova and Mikova (2019) and Teplova and Gurov (2022) find that illiquidity has a significant effect on the pricing of Russian stocks. It is worth noting that nowadays, there is no consensus on whether a high trading volume is associated with higher systematic and downside risk. However, Hrdlicka (2022) demonstrates that high-beta US stocks have more rebalancing, and this relationship is statistically and economically significant. At the same time, Hrdlicka (2022) categorizes trading volume as a dependent variable, whereas beta is modeled as an explanatory variable. Chen et al. (2001) show that an increase in trading volume relative to a 6-month trend generates more pronounced negative skewness in stock returns. At the same time, some authors (e.g., He et al. 2017) find that trading volume has different prediction effects for downside risk in different periods in the Chinese stock market. Therefore, we put forward Hypothesis 1:

H1: *Of the explanatory non-ESG variables, the indicators of stock liquidity have the greatest impact on downside and systematic risks. The greater relative bid–ask spread and Hui Heubel illiquidity measure, the lower the dependent risk variables. The lower the free float, the lower the dependent risk variables.*

Based on empirical results, Teplova et al. (2023) develop policy implications for countries with major environmental problems: "Improvement in ESG factors is beneficial in the long run and during the crisis periods because it can reduce company-specific risk and increase stock liquidity". Therefore, we put forward Hypothesis 2:

H2: *Indicators of ecological responsibility are negatively and statistically significantly associated with stock-specific measures of systematic and downside risks (beta and downside beta, respectively).*

Teplova et al. (2023) show that social responsibility is a factor affecting the liquidity of Russian stocks and can be considered "a "business card" of Russian public companies". Yet, the authors show that during COVID-19, social responsibility was not among the determinants of stock liquidity. Therefore, we put forward Hypothesis 3:

H3: *Among different ESG characteristics of Russian public companies, social responsibility had the most significant negative impact on stock-specific downside and systematic risks before COVID-19.*

Teplova et al. (2023) demonstrate that the impact of environmental factors on the liquidity of Russian stocks has changed direction from negative to positive during COVID-19 and attribute this result to changes in investor preferences: they began to consider Russian green stocks to be defensive assets. Lashkaripour (2023) finds that investors kept holding green US stocks in their portfolios during the COVID-19 crisis. The author suggests that the non-pecuniary motive for ESG investing among US investors stayed strong, and the utility loss from negative shocks to wealth was lower than the benefit of ESG investing. At the same time, put options on high-ESG stocks became more expensive during the crisis, which reflected investor expectations of a future significant price decline of green stocks. This explains both the resiliency of high-ESG US assets and their growing tail risk. At the same time, Lööf et al. (2022) demonstrate that higher ESG ratings led to a reduction in tail risk during COVID-19 for green stocks. So, the results of the possible impact of the COVID-19 pandemic on the relationship between ESG indicators and downside and systematic risks are mixed. In addition to the baseline specifications, it makes sense to test whether the effect of ESG on downside risk is related to the COVID-19 pandemic, which leads to Hypothesis 4.

H4: *During and before the COVID-19 pandemic, downside and systematic risks for companies with the same level of ESG rating were identical. In other words, the COVID-19 crisis did not affect the relationship between ESG and these two risks across all ESG categories.*

Table 1 provides a summary of the variables used in this research and their expected signs.

Table 1. Expected signs of the influence of explanatory variables used in research on beta and downside beta.

Name	Description	Expected Sign
Net_debt_EBITDA	Net debt/EBITDA	+
ROE	Return on equity	−
ICR	Interest coverage ratio	−
ROA	Return on assets	−
Operat_margin	Operating margin	−
Tobin's_Q	Tobin's Q (the ratio of market capitalization to net asset value)	−
Revenue_growth	Revenue growth, %, year to year	−
Social_score	Social responsibility score (0 at minimum, 100 at maximum)	−
Govern_score	Corporate governance score (0 at minimum, 100 at maximum)	−
Emiss_score	A measure of a company's commitment to reduce emissions in its production and operational processes (0 at minimum, 100 at maximum)	−
Ln_Env_innov_score	A logged measure of a company's propensity to environmental innovations (0 at minimum when $Env\_innov\_score = 0$ and $\ln 100$ at maximum)	−
Ln_Policy_water_score	A logged measure of a company's water withdrawal (0 at minimum when $Policy\_water\_score = 0$ and $\ln 100$ at maximum)	−
Ln_Policy_energy_score	A logged measure of sustainability in a company's energy policy (0 when $Policy\_energy\_score = 0$ and $\ln 100$ at maximum)	−
Policy_emiss_score	A measure of sustainability in a company's emissions policy (0 at minimum, 100 at maximum)	−
Env_manag_team_score	A measure of the effectiveness of a company's environmental management (0 at minimum, 100 at maximum)	−
Env_supp_chain_score	A measure of sustainability in a company's supply chain management (0 at minimum, 100 at maximum)	−
Rel_spread	Relative monthly bid–ask spread: average for the months of a specific year	+
Ln_Trad_volume	Logarithm of monthly trading volume, not taking into account free float: average for the months of a specific year	+ or −
Free_float	Monthly free float: average for the months of a specific year	−
Ln_one_plus_ Hui Heubel	Logarithm of 1 plus monthly Hui Heubel measure: average for the months of a specific year	+

Note. In the column «Expected sign» «+» indicates a positive impact of a factor on the dependent variable, «−» indicates a negative impact.

3.2. Empirical Methodology

To test Hypotheses 1 and 2, we use the following baseline specifications:

$$y_{it}^{j} = \beta_0^{j} + \beta^{j} X_{it} + \varepsilon_{it}^{j} \tag{1}$$

where y_{it}^{j} $(j = 1,\ 2)$ is an $NT \times 1$ vector which represents one of the two dependent variables, daily downside beta or daily beta measured for year t and stock i, and X_{it} is an $NT \times K$ matrix which represents observations on the explanatory variables.

The pooled regression involves estimating a single equation on all the data together. We employ neither the firm fixed effects nor the year fixed effects since the number of observations is not sufficient to increase the number of the degrees of freedom.

Specification (2) with an interaction term between the dummy variable *COVID_19* and one of the ESG factors is used to test Hypotheses 3 and 4:

$$\begin{gathered} y_{it}^{j} = \beta_0^{j} + \beta_1^{j,l} 1\{COVID\text{-}19\}_t + \beta_2^{j,l} Z_{it}^{j,l} + \beta_3^{j} 1\{COVID\text{-}19\}_t \times Z_{it}^{j,l} + \\ \sum_k \beta_k^{j,l} W_{it} + \varepsilon_{it}^{j,l}, \end{gathered} \tag{2}$$

where $1\{COVID\text{-}19\}_t$ is an indicator that year t is either 2020 or 2021; $Z_{it}^{j,l}$ $(j = 1,\ 2;$ $l = 1, \ldots, 9)$ is one of the nine ESG scores included in the final sample (*Social_score*, *Govern_score*, *Emiss_score*, *Ln_Env_innov_score*, *Ln_Policy_water_score*, *Ln_Policy_energy_score*, *Policy_emiss_score*, *Env_manag_team_score*, *or Env_supp_chain_score*); and W_{it} are all non-ESG explanatory variables included in the final sample (control variables).

We do not include interaction terms between $1\{COVID\text{-}19\}_t$ and all ESG variables in (2) simultaneously because of the arising severe multicollinearity.

Now, we briefly describe the meanings of the parameters β_0^{j}, $\beta_1^{j,l}$, $\beta_2^{j,l}$, and β_3^{j}. The estimate of $\beta_0^{j,l}$ is the intercept for the group of observations corresponding to the pre-COVID-19 period. The estimate of $\beta_1^{j,l}$ is a difference in the intercepts between the group of observations corresponding to the COVID-19 pandemic and the group of observations corresponding to the period from 2013 to 2019. The estimate of $\beta_2^{j,l}$ is the slope of the ESG factor for the pre-COVID-19 period. It shows a change in a dependent variable (either beta or downside beta) associated with a unit growth in an ESG factor. The estimate of $\beta_3^{j,l}$ measures a difference in the slopes between the group of observations corresponding to the COVID-19 pandemic and the group of observations corresponding to the period from 2013 to 2019. Thus, it demonstrates a difference in changes in a risk measure after a unit increase in the considered ESG variable. In terms of model (2), Hypothesis 3 implies that the null hypothesis that two estimated coefficients $\beta_2^{j,l}$ $(j = 1,\ 2)$ for the variable *Social_score* are zero is strongly rejected. Hypothesis 4 in turn states that $\beta_1^{j,l} = 0$ and $\beta_3^{j,l} = 0$.

3.3. Descriptive Statistics on the Sample

We apply a 90% winsorization for each explanatory variable from the initial set. All data below the 5th percentile are set to the 5th percentile, and the data above the 95th percentile are set to the 95th percentile. Next, we remove all explanatory variables that are highly correlated with several other variables, ensuring all pairwise correlations are under 0.7; this threshold is encountered in many research articles and econometrics books as an approximate boundary between strong and medium levels of correlation (e.g., Ratner 2009).

The descriptive statistics are presented in Table 2. Though the variance inflation factors are above 10 (but lower than 19) for some ESG variables, we keep them in the final dataset since Specification 2 does not include all these variables simultaneously. By doing so, we can also check whether the results of fitting Specification 1 are consistent with the empirical evidence implied by Specification 2.

Table 2. Sample statistics.

Variables	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
Down_beta	0.8966	0.8474	2.6735	−0.3870	0.4539	0.8128	1.8696
Beta	0.7887	0.7605	1.9401	−0.0846	0.3661	0.3483	0.0672
Net_debt_EBITDA	1.651	1.290	18.332	−0.738	1.926	3.418	21.036
ROE	0.166	0.123	1.969	−1.500	0.373	0.065	8.077
ICR	12.167	7.581	140.944	−3.000	13.812	3.440	26.057
ROA	6.931	5.822	35.000	−15.860	8.424	0.320	1.562
Operat_margin	15.162	13.060	55.622	−15.000	15.439	0.807	0.285
Tobin's_Q	1.434	1.089	7.000	−0.021	1.195	2.769	9.555
Revenue_growth	5.316	2.828	70.000	−45.000	16.733	0.592	1.953
Social_score	43.667	42.408	88.032	0.368	22.158	0.086	−0.996
Govern_score	50.951	50.995	96.390	5.046	22.429	−0.066	−1.054
Emiss_score	50.865	55.441	94.412	0.000	24.717	−0.519	−0.689
Ln_Env_innov_score	1.2161	0.0000	4.590	0.000	1.769	0.823	−1.247
Ln_Policy_water_score	3.526	4.254	4.422	0.000	1.628	−1.714	0.955
Ln_Policy_energy_score	3.513	4.206	4.387	0.000	1.603	−1.742	1.061
Policy_emiss_score	52.234	62.407	76.683	0.000	26.488	−1.366	0.124
Env_manag_team_score	42.322	69.091	89.749	0.000	36.895	−0.260	−1.902
Env_supp_chain_score	29.687	0.0000	86.462	0.000	37.423	0.485	−1.740
Rel_spread	0.147	0.123	0.862	0.022	0.103	2.438	10.474
Ln_Trad_volume	7.708	7.724	12.237	4.352	1.364	0.018	0.352
Free_float	33.676	29.226	100.000	4.004	21.622	1.162	1.070
Ln_one_plus_Hui Heubel	2.278	1.965	6.582	0.345	1.151	0.969	0.764

Note: Table 2 presents sample statistics for two dependent variables, daily downside beta (*Down_beta*) and daily beta (*Beta*), and for the following explanatory variables: the net debt-to-EBITDA ratio (*Net_debt_EBITDA*), ROE (*ROE*), ICR (*ICR*), ROA (*ROA*), operating margin (*Operat_margin*), Tobin's Q (*Tobin's_Q*), revenue growth (*Revenue_growth*), social responsibility score (*Social_score*), corporate governance score (*Govern_score*), emissions score (*Emiss_score*), the logarithm of environmental innovation score (*Ln_Env_innov_score*), the logarithm of policy water score (*Ln_Policy_water_score*), the logarithm of policy energy score (*Ln_Policy_energy_score*), policy emissions score (*Policy_emiss_score*), environmental management team score (*Env_manag_team_score*), environmental supply chain management (*Env_supp_chain_score*), average relative bid–ask spread (*Rel_spread*), the average logarithm of trading volume (*Ln_Trad_volume*), average free float ratio (*Free_float*), and the average logarithm of one plus Hui Heubel measure (*Ln_one_plus_Hui Heubel*). The sample period is 2013–2021. The number of year–firm observations is 280.

4. Results and Discussion

Table 3 shows the results of running pooled regression (1). The heteroskedasticity-consistent standard errors were corrected for the presence of general forms of temporal and spatial correlation (Driscoll–Kraay standard errors).

To alleviate the potential multicollinearity problem, we discard the insignificant regressors from the model by following the necessary and sufficient criteria for improving the adjusted R^2 (Rao 1976). The corresponding results are given in Table 4.

Tables 5 and 6 provide the results of regressions (2), where the dependent variable is $Down\_beta \times 10^3$ (downside beta multiplied by 1000) and $Beta \times 10^3$ (beta multiplied by 1000), respectively.

4.1. Testing Hypothesis 1 about the Impact of Non-ESG Factors on Downside and Systematic Risk

Our results partly support Hypothesis 1. On the one hand, the logarithm of trading volume is one of the most significant variables across all specifications. We also find that the free float ratio has a significant impact on downside beta across almost all specifications. On the other hand, other proxies for stock liquidity, such as the logarithm of one plus the Hui Heubel measure or relative bid–ask spread, are insignificant regressors across most of the specifications.

Table 3. Baseline specifications.

	Down_beta $\times$ **10**^{3}	***Beta*** $\times$ **10**^{3}
Intercept	500.38 * (290.55)	255.02 (272.66)
Net_debt_EBITDA	−5.76 (17.48)	−18.18 * (10.20)
ROE	−178.06 *** (40.58)	−201.59 *** (26.56)
ICR	−2.85 *** (1.01)	−1.17 (1.11)
ROA	0.20 (4.78)	0.26 (3.42)
Operat_margin	−1.81 (4.21)	−2.69 (2.84)
Tobin s_Q	−24.51 *** (6.86)	−27.38 *** (5.47)
Revenue_growth	−0.69 (2.44)	0.12 (2.31)
Social_score	−0.40 (1.50)	1.59 (1.24)
Govern_score	0.07 (0.85)	0.75 (0.49)
Emiss_score	2.52 ** (1.27)	2.50 * (1.32)
Ln_Env_innov_score	−19.59 * (10.24)	−41.23 *** (4.81)
Ln_Policy_water_score	−0.09 (21.85)	−24.52 * (13.69)
Ln_Policy_energy_score	−50.01 *** (16.16)	−16.27 * (8.36)
Policy_emiss_score	1.85 ** (0.76)	1.46 ** (0.71)
Env_manag_team_score	−0.08 (0.22)	0.74 * (0.44)
Env_supp_chain_score	−1.19 *** (0.41)	−1.20 *** (0.38)
Rel_spread	589.53 (407.65)	543.12 * (282.94)
Ln_Trad_volume	70.98 *** (15.27)	59.51 *** (10.32)
Free_float	−1.14 (1.22)	2.95 *** (0.58)
Ln_one_plus_Hui Heubel	−48.11 (35.62)	−27.32 (23.58)
Number of observations	280	280
Adj. R-squared	0.131	0.190
Durbin–Watson statistic	1.910	1.739

Note: The Driscoll–Kraay robust standard errors are in parentheses (the Bartlett kernel and a default lag length are used to calculate the covariance matrix); *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Adjusted R-squared shows the percent of the variance in the outcome explained by the model adjusted for the number of predictors in the model.

Table 4. Baseline specification: simultaneous removal of insignificant regressors following Rao (1976).

	$Down\_beta \times 10^3$	$Beta \times 10^3$
Intercept	413.97 ** (198.98)	222.16 (285.42)
Net_debt_EBITDA		−14.42 *** (4.93)
ROE	−214.08 *** (65.06)	−192.83 *** (19.81)
ICR	−2.50 ** (1.17)	
ROA		
Operat_margin		−2.67 (2.56)
Tobin's_Q		−27.58 *** (6.66)
Revenue_growth		
Social_score		1.54 (1.26)
Govern_score		0.83 (0.69)
Emiss_score	2.18 (1.37)	2.43 * (1.39)
Ln_Env_innov_score	−13.81 ** (5.92)	−39.02 *** (4.24)
Ln_Policy_water_score		−25.64* (15.50)
Ln_Policy_energy_score	−47.64 *** (12.16)	−13.82 (10.09)
Policy_emiss_score	1.93 *** (0.44)	1.39 * (0.72)
Env_manag_team_score		0.72 (0.50)
Env_supp_chain_score		−1.21 *** (0.39)
Rel_spread	589.90 (372.14)	562.05 * (286.16)
Ln_Trad_volume	78.10 *** (10.66)	60.26 *** (11.00)
Free_float		3.00 *** (0.64)
Ln_one_plus_Hui Heubel	−58.03 ** (26.57)	−26.12 (24.75)
Number of observations	280	280
Adj. R-squared	0.154	0.198
Durbin–Watson statistic	1.899	1.740

Note: The Driscoll–Kraay robust standard errors are in parentheses (the Bartlett kernel and a default lag length are used to calculate the covariance matrix); *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Adjusted R-squared shows the percent of the variance in the dependent variable explained by the model adjusted for the number of predictors in the model. The subsets of independent variables are selected based on the necessary and sufficient criteria for removing variables described in Rao (1976).

Table 5. Specifications with an interaction term: $Down\_beta \times 10^3$.

	$Down\_beta \times 10^3$, $Social\_score$	$Down\_beta \times 10^3$, $Govern\_score$	$Down\_beta \times 10^3$, $Emiss\_score$	$Down\_beta \times 10^3$, $Ln\_env\_innov\_score$	$Down\_beta \times 10^3$, $Ln\_policy\_water\_score$	$Down\_beta \times 10^3$, $Ln\_policy\_energy\_score$	$Down\_beta \times 10^3$, $Policy\_emiss\_score$	$Down\_beta \times 10^3$, $Env\_manag\_team\_score$	$Down\_beta \times 10^3$, $Env\_supp\_chain\_score$
Intercept	546.45 ** (242.71)	487.04 ** (203.55)	313.77 (255.32)	538.53 *** (207.12)	468.98 ** (228.97)	497.00 *** (167.17)	321.86 (244.13)	470.91 ** (220.97)	489.89 ** (223.39)
Dummy for COVID-19	−256.04 * (132.28)	288.90 *** (100.25)	−192.32 (152.64)	−255.02 ** (119.02)	−592.67 *** (167.13)	−616.46 *** (108.92)	−60.21 (161.08)	−219.35 * (129.49)	−148.14 (116.35)
Interaction term	1.92 (1.20)	2.30 *** (0.70)	0.04 (1.85)	43.17 * (16.76)	104.22 *** (20.17)	111.72 *** (17.21)	−1.98 (2.33)	1.27 ** (0.60)	−0.17 (0.54)
Net_debt_EBITDA	10.00 (18.18)	11.17 (18.75)	11.94 (19.17)	8.05 (18.06)	10.94 (19.24)	11.86 (16.91)	10.29 (18.11)	11.27 (18.94)	9.54 (19.39)
ROE	−125.31 *** (38.07)	−137.81 *** (39.61)	−131.03 *** (40.42)	−139.61 *** (40.44)	−128.18 *** (39.43)	−132.67 *** (37.90)	−134.34 *** (36.13)	−133.65 *** (38.62)	−124.92 *** (39.54)
ICR	0.04 (1.59)	−0.22 (1.59)	−0.16 (1.55)	−0.40 (1.68)	−0.06 (1.66)	1.36 (1.08)	−0.64 (1.42)	−0.01 (1.60)	−0.09 (1.56)
ROA	−0.14 (3.94)	−0.21 (3.99)	−0.17 (4.30)	0.55 (3.58)	−0.41 (4.15)	0.23 (4.02)	0.09 (4.27)	−0.28 (4.08)	−0.47 (4.14)
Operat_margin	−2.89 (4.33)	−2.64 (4.50)	−2.98 (4.53)	−4.53 (4.93)	−2.85 (4.69)	−3.12 (4.34)	−2.71 (4.58)	−2.40 (4.22)	−2.95 (4.57)
Tobin's_Q	−17.67 * (10.25)	14.78 (10.46)	−14.31 (9.63)	−23.13 ** (10.22)	−17.44 * (8.88)	−20.20 * (10.74)	−14.96 (9.90)	−16.55 * (9.98)	−15.49 * (9.36)
Revenue_growth	−1.58 (2.47)	−1.62 (2.42)	−1.59 (2.59)	−1.42 (2.51)	−1.48 (2.35)	−1.77 (2.51)	−1.42 (2.54)	−1.63 (2.45)	−1.57 (2.51)
Social_score	−1.72 (1.26)								
Govern_score		−0.85 (0.55)							
Emiss_score			1.48 * (0.86)						
Ln_Env_innov_score				−37.66 ** (18.76)					
Ln_Policy_water_score					−4.82 (13.76)				
Ln_Policy_energy_score						−26.26 *** (7.79)			
Policy_emiss_score							1.43 * (0.73)		
Env_manag_team_score								−0.59 (0.62)	
Env_supp_chain_score									−0.49 (0.62)
Rel_spread	522.98 (400.96)	599.06 (397.15)	712.11 (450.85)	507.70 (372.20)	627.31 (391.87)	548.83 (379.69)	684.23 (424.74)	588.77 (413.48)	585.72 (403.16)
Ln_Trad_volume	78.22 *** (14.53)	80.99 *** (14.47)	83.98 *** (14.46)	79.67 *** (13.93)	80.28 *** (14.66)	83.14 *** (13.73)	85.40 *** (15.18)	78. 85 *** (14.15)	76.38 *** (15.27)
Free_float	0.61 (0.94)	0.43 (1.03)	0.66 (0.96)	0.50 (0.95)	0.44 (0.91)	0.60 (0.92)	0.45 (0.91)	0.69 (0.96)	0.60 (0.99)
Ln_one_plus_Hui Heubel	−68.57 * (37.65)	−67.79 * (37.90)	−61.79 * (37.25)	−60.65 (40.17)	−69.23 * (36.96)	−60.68 (37.77)	−64.80 * (35.16)	−67.53 * (37.63)	−67.40 * (38.76)
Number of observations	280	280	280	280	280	280	280	280	280
Adj. R-squared	0.131	0.129	0.132	0.139	0.133	0.139	0.132	0.129	0.128
Durbin-Watson statistic	1.856	1.820	1.838	1.886	1.855	1.848	1.844	1. 851	1.846
$H0: Dummy\ for\ COVID$-19 = 0, $Interaction\ term = 0$	W = 3.899 (0.142)	W = 32.371 (0.000)	W = 3.016 (0.221)	W = 7.719 (0.021)	W = 26.923 (0.000)	W = 61.533 (0.000)	W = 2.772 (0.250)	W = 4.557 (0.103)	W = 3.184 (0.204)

Note: The Driscoll–Kraay robust standard errors are in parentheses (the Bartlett kernel and a default lag length are used to calculate the covariance matrix); *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Adjusted R-squared shows the percent of the variance in the outcome explained by the model adjusted for the number of predictors in the model. The last row demonstrates the results of the Wald test of the null hypothesis that $Dummy\ for\ COVID$-19 = 0 and $Interaction\ term = 0$ (p-values are in parentheses).

Table 6. Specifications with an interaction term: $Beta \times 10^3$.

	$Beta \times 10^3$, Social_score	$Beta \times 10^3$, Govern_score	$Beta \times 10^3$, Emiss_score	$Beta \times 10^3$, Ln_env_innov_score	$Beta \times 10^3$, Ln_policy_water_score	$Beta \times 10^3$, Ln_policy_energy_score	$Beta \times 10^3$, Policy_emiss_score	$Beta \times 10^3$, Env_manag_team_score	$Beta \times 10^3$, Env_supp_chain_score
Intercept	285.03 (216.14)	269.23 * (160.69)	137.71 (217.15)	496.25 *** (142.88)	411.47 ** (177.31)	277.36 (189.88)	235.53 (205.81)	288.76 (201.45)	386.02 ** (182.19)
Dummy for COVID-19	−125.39 (171.14)	−113.59 (139.37)	−134.30 (158.63)	−144.30 (108.47)	−507.97 *** (175.29)	−561.66 *** (174.79)	−65.30 (141.18)	−99.77 (139.09)	−83.77 (136.58)
Interaction term	0.61 (1.58)	0.72 (0.61)	0.28 (1.46)	32.79 *** (11.53)	105.65 *** (2.23)	116.91 *** (29.46)	−0.44 (1.63)	0.15 (0.84)	0.20 (0.91)
Net_debt_EBITDA	−8.41 (7.24)	−8.96 (6.75)	−8.68 (7.06)	−14.70 ** (6.41)	−10.18 (6.46)	−6.23 (5.84)	−11.24 ** (5.63)	−5.91 (8.20)	−10.18 (6.44)
ROE	−143.82 *** (26.49)	−133.71 *** (26.91)	−135.96 *** (32.49)	−150.64 *** (30.05)	−132.88 *** (31.08)	−127.93 *** (29.85)	−140.76 *** (26.07)	−151.30 *** (25.07)	−134.02 *** (28.67)
ICR	0.98 (1.37)	1.17 (1.54)	0.69 (1.21)	0.21 (1.45)	0.93 (1.28)	3.02 ** (1.30)	0.32 (1.13)	0.81 (1.32)	0.98 (1.22)
ROA	−1.15 (2.78)	−0.63 (2.54)	−1.00 (3.27)	−0.18 (2.51)	−1.28 (2.84)	−1.45 (2.73)	−0.71 (3.02)	−0.80 (2.91)	−1.20 (2.97)
Operat_margin	−1.31 (3.30)	−1.60 (3.16)	−1.79 (3.08)	−3.34 (3.11)	−1.53 (3.22)	−1.72 (2.91)	−1.35 (3.07)	−1.89 (2.77)	−1.48 (3.13)
Tobin′s_Q	−13.90 ** (6.78)	−17.64 *** (5.54)	−12.13 * (6.82)	−22.68 *** (7.30)	−16.51 ** (8.13)	−24.76 *** (6.71)	−14.05 *** (4.81)	−11.81 (7.87)	−14.35 * (7.75)
Revenue_growth	−0.58 (2.24)	−0.50 (2.26)	−0.58 (2.35)	−0.35 (2.22)	−0.48 (2.04)	−0.81 (2.35)	−0.45 (2.27)	−0.35 (2.08)	−0.56 (2.23)
Social_score	1.17 (1.42)								
Govern_score		1.21 *** (0.43)							
Emiss_score			2.73 ** (1.15)						
Ln_Env_innov_score				−41.51 *** (12.65)					
Ln_Policy_water_score					−6.86 (13.90)				
Ln_Policy_energy_score						7.49 (11.25)			
Policy_emiss_score							1.63 * (0.85)		
Env_manag_team_score								1.02 (0.82)	
Env_supp_chain_score									−0.18 (0.81)
Rel_spread	482.17 * (289.26)	473.36 (291.08)	556.93 * (328.92)	262.83 (215.61)	391.83 (249.06)	466.39 * (276.29)	466.19 (294.09)	488.63 (313.48)	385.21 (268.86)
Ln_Trad_volume	64.13 *** (9.37)	63.21 *** (10.46)	68.05 *** (7.64)	59.42 *** (10.32)	61.01 *** (11.20)	65.74 *** (11.79)	67.23 *** (8.17)	66.35 *** (8.93)	60.21 *** (9.67)
Free_float	2.73 *** (0.60)	3.09 *** (0.62)	2.96 *** (0.61)	2.72 *** (0.61)	2.67 *** (0.64)	2.65 *** (0.60)	2.65 *** (0.58)	2.62 *** (0.58)	2.82 *** (0.62)
Ln_one_plus_Hui Heubel	−46.41 * (25.20)	−46.22 * (25.50)	−36.16 (23.59)	−40.29 (25.93)	−49.25 *** (24.24)	−44.48 * (26.67)	−43.61 * (23.00)	−50.03 * (25.04)	−47.57 * (26.26)
Number of observations	280	280	280	280	280	280	280	280	280
Adj. R-squared	0.145	0.147	0.169	0.162	0.150	0.157	0.152	0.149	0.140
Durbin-Watson statistic	1.660	1.683	1.671	1.761	1.728	1.680	1.689	1.676	1.717
H0: Dummy for COVID-19 = 0, Interaction term = 0	W = 0.653 (0.721)	W = 1.381 (0.501)	W = 1.226 (0.542)	W = 8.524 (0.014)	W = 24.304 (0.000)	W = 15.911 (0.000)	W = 0.699 (0.705)	W = 1.243 (0.537)	W = 0.631 (0.729)

Note: The Driscoll–Kraay robust standard errors are in parentheses (the Bartlett kernel and a default lag length are used to calculate the covariance matrix); *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Adjusted R-squared shows the percent of the variance in the outcome explained by the model adjusted for the number of predictors in the model. The last row demonstrates the results of the Wald test of the null hypothesis that both $Dummy\ for\ COVID$-19 = 0 and $Interaction\ term = 0$ (p-values are in parentheses).

Among financial performance indicators, the net debt-to-EBITDA ratio, ROE, and the Tobin's Q have the most significant impact on beta and downside beta. It is worth noting that we reveal an unexpected (negative) direction of influence on risk measures from Net Debt/EBITDA.

The academic literature provides evidence for the influence of financial leverage on systematic risk measured by market betas (e.g., John et al. 1994; Campbell et al. 2011). Positive and significant relationships between leverage and firm systematic risks are found in many research articles (e.g., Hamada 1972; Damodaran 2009; Adhikari 2015). At the same time, some authors (e.g., Omet and Al-Debi'e 2000) demonstrate the weak association between market betas and financial leverage for some companies. The unexpected relationship between debt burden (the Net Debt-to-EBITDA ratio) and measures of systematic (beta) and downside (downside beta) risks can be considered a risk anomaly in the Russian stock market. Baker et al. (2020) show how the risk anomaly theory can explain why leverage can be inversely related to systematic risk, holding the total risk constant as well as downside risk. A thorough analysis of the possible causes of this effect is a direction for future research.

Interestingly, we find that ROE, unlike ROA, has a statistically significant negative effect on a dependent variable almost in all specifications. It is important to take into account that ROE depends both on ROA and the debt-to-equity ratio, so ROE can be simply increased by using financial leverage. However, shareholders' profits become more volatile in this case. So, we find indirectly that a higher debt burden is associated with weaker systematic and downside risks, which corresponds to the above-mentioned anomalous relationship between the net debt-to-EBITDA ratio and downside and systematic risks.

According to our empirical results, a high trading volume is associated with a growth in beta and downside beta. It is well known that many stock market crises feature extremely high trading volumes and record realized return volatility. Over 2013–2021, the Russian stock market experienced a lot of significant drawdowns (e.g., the two-day destabilization in the Russian foreign exchange market in mid-December 2014 and the contemporaneous stock market crisis) characterized by spikes in the trading volume. Therefore, since there have been many high-volume events in the Russian stock market, the trading volume not adjusted for realized volatility can be considered a proxy for market turbulence rather than a measure of liquidity. The results also indicate that the tightness and resiliency proxied by the bid–ask spread and the logarithm of one plus the Hui Heubel measure are important dimensions of liquidity in terms of their impact on the systematic risk measures in some specifications. Nevertheless, the statistical significance is lower compared to the trading volume.

It is also worth noting that the results of fitting model (2) (with the interaction term) provide similar conclusions regarding the impact of different fundamental and non-fundamental variables.

4.2. Testing Hypothesis 2 about the Negative Impact of Factors of Ecological Responsibility on Downside and Systematic Risks

Hypothesis 2 is partly confirmed. Among the seven metrics of ecological responsibility (Emiss_score, Ln_Env_innov_score, Ln_Policy_water_score, Ln_Policy_energy_score, Policy_emiss_score, Env_manag_team_score, Env_supp_chain_score), a logged measure of a company's propensity to environmental innovations, a logged measure of a company's water withdrawal, and a measure of sustainability in a company's supply chain management have a significant negative influence on beta for Specification 1 (also after eliminating insignificant regressors following Rao 1976). This finding contradicts the results of Teplova et al. (2023) to some extent. The authors find that publicly traded stocks of Russian companies that overlook the water withdrawal policy are more illiquid and explain this by the fact that "the reduction in the use of water requires technological innovations that are costly for companies and lead to an increased company-specific risk in the short-run, which decreases stock liquidity". We also demonstrate that a measure of a company's commitment to reduce emissions in its production and operational processes and a measure of sustainability in a company's emissions policy have a positive impact on beta. One possible explanation for this finding is that it can be particularly costly for the considered sample of Russian public companies to raise the level of sustainability in their emissions policies.

Similar conclusions are valid in the case of using downside beta as a dependent variable in model (1). A measure of sustainability in a company's emissions policy have a significant positive influence on this variable; a logged measure of a company's propensity to environmental innovations and a logged measure of sustainability in a company's energy policy constitute the subset of variables which have a negative impact on downside beta. The results remain robust after applying the procedure of eliminating regressors from the model.

4.3. Testing Hypothesis 3 about the Significance of the Impact of Social Responsibility on Downside and Systematic Risks

Hypothesis 3 is rejected: Social_score does not have a statistically significant (even at the 10% level) influence on either beta or downside beta before the COVID-19 crisis. Among other ESG factors, only *Ln_Env_innov_score* and *Policy_emiss_score* have a significant influence on both beta and downside beta during the period from 2013 to 2019 (negative and positive impact, respectively). The results contrast with the findings of Teplova et al. (2023) who demonstrate that social responsibility enhanced stock liquidity before the pandemic.

4.4. Testing Hypothesis 4 about the Significance of the Impact of COVID-19 on the Relationship between ESG and Risks

Hypothesis 4 is partly confirmed. We find that the influence of the pandemic on the relationship between ESG and downside and systematic risks is not straightforward. Judging by the results of the Wald test that assesses the constraints on statistical parameters $\beta_1^{j,l} = 0$ and $\beta_3^{j,l} = 0$, Hypothesis 4 is rejected at the 10% significance level for 7 out of 18 cases (see the last rows in Tables 5 and 6). Let us discuss some of these cases.

The average downside beta was not statistically identical for stocks with the same level of *Ln_Policy_water_score* (a logged measure of a company's water withdrawal score) before and during the pandemic. Not only was downside beta significantly lower during the crisis for stocks of companies with minimal water withdrawal scores, but also the reduction in this gap, as *Ln_Policy_water_score* increases, was statistically significant during the COVID-19 crisis. Also, the results of the Wald test indicate that average beta was not statistically the same for stocks with similar levels of *Ln_Policy_water_score* before and during the COVID-19 crisis. The same is true for the sustainability of energy policy (*Ln_policy_energy__score).*

In almost all cases where Hypothesis 4 was rejected, we found that higher ESG ratings led to a statistically significant growth of either downside beta or beta during COVID-19. These results are in line with the findings of Lashkaripour (2023), who reveal a significant rise in tail risk for US green stocks during the COVID-19 crisis. The same effect is observed for corporate governance scores during the COVID-19 pandemic.

5. Conclusions

We contribute to the literature by identifying the determinants of downside and systematic risks in the emerging Russian stock market over the period from 2013 to 2021. Different panel regression methods are used to estimate the influence of non-fundamental ESG factors, different financial indicators of public companies, and stock liquidity measures on stock-specific betas and downside betas. We also zoom in on the exogenous COVID-19 crisis, which caused a massive disruption of supply chains, by using the specifications with multiplicative variables to determine changes in the impact of ESG factors during the pandemic.

A company's propensity to environmental innovations leads to a decrease in both systematic and downside risks; this conclusion remains valid in the case of using different regression models. The reduction in emissions leads to higher betas, which we explain by the fact that these measures can be costly for firms.

We show that the logarithm of the trading volume is significant for the dependent risk variables for all specifications. Among financial performance indicators, the net debt-to-EBITDA ratio, Tobin's Q, and ROE have the most crucial impact on dependent variables. An unexpected result is that a higher debt burden is associated with lower levels of systematic and downside risks, which can be considered an anomaly in the Russian stock market.

The first theoretical implication is the impact of ESG indicators on systematic and downside risk in a large emerging stock market. Not only a company's financial indicators but also ESG indicators and stock liquidity proxies are significant for systematic and downside risks. Researchers, analysts, and investors should pay attention to ESG factors when developing investment strategies, building portfolios, or modeling the trade characteristics of stocks in the Russian stock market.

The second implication is that our approach allows us to reveal the role of different determinants in periods of macroeconomic stability and the COVID-19 pandemic. During this crisis, the favorable impact of implementing environmental innovations on downside risk and systematic risk decreased. This finding is valid for some other environment-related measures as well (sustainable water policy and sustainability in a company's supply chain management). A company's stakeholders should pay special attention to these factors during financial turmoil.

Our findings have practical implications for retail and institutional investors, fund managers, corporate managers, and policymakers. Investors and fund managers, when choosing stocks for their portfolios, should pay attention not only to issuer fundamentals but also to ESG factors and take into account the macroeconomic background. If investors forecast a decline in the Russian stock market or their intention is to build a protective portfolio with a low level of systematic risk, they should choose companies with high ROE and Tobin's Q. They should not implement costly environmental innovations at times of financial turmoil. In contrast, an investor predicting a stock market boom or aimed at building a 'high yield-high risk' portfolio should choose companies with low ROE and Tobin's Q, as well as a sustainable emissions policy. Investors also should take into account the fact that different dimensions of stock liquidity can influence systematic and downside risks differently. While our findings provide some insights on investment decisions, investors should do their due diligence in investing because the investment climate is dynamic, firm performance can change, and past performance does not guarantee similar outcomes in the future.

Corporate managers are recommended to limit the debt burden (provide sustainable funding) and adhere to a balanced policy regarding implementing environmental innovations. The emerging Russian stock market is characterized by a high share of companies in the oil and gas sector, metallurgy, and manufacturing sectors. For these sectors, environmental protection can ensure sustainable development in the long run. However, it is costly in the short run, so stocks of companies implementing environmental innovations can be associated with increased downside risk in a period of financial turmoil.

Policymakers (the government and ministries) can play an important role in encouraging companies to implement the above-mentioned ESG-compliant practices by providing financial incentives and setting regulatory barriers.

The findings also provide novel implications for risk management with ESG considerations during crises. We demonstrate that ESG considerations can increase downside or systematic risks during market crises.

A limitation of our research is the relatively small sample size. Investigating the determinants of systematic and downside risks across a wider range of Russian stocks, including mid-cap and small-cap ones, would be interesting for future research. In addition, another possible direction for future studies is to use ESG indicators from different agencies.

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Notes

1 EBA Report on Management and Supervision of ESG risks for Credit Institutions and Investment Firms (2021). EBA/REP/2021/18. https://www.eba.europa.eu/sites/default/files/document_library/Publications/Reports/2021/1015656/EBA%20Report%20on%20ESG%20risks%20management%20and%20supervision.pdf (accessed on 1 April 2024).

2 https://www.statista.com/statistics/573701/market-cap-of-domestic-companies-as-share-of-gdp-russia/ (accessed on 1 April 2024).

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