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Environmental Performance and Corporate Earnings Per Share: Evidence from the Warsaw Stock Exchange

Efektywność środowiskowa a zysk na akcję przedsiębiorstw – wyniki z Giełdy Papierów Wartościowych w Warszawie

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Abstract

Reducing carbon dioxide (CO_2) and other greenhouse gas (GHG) emissions is of paramount importance because of their role in trapping atmospheric heat, a process that leads to global temperature increases commonly referred to as global warming. Rising temperatures, in turn, catalyse climate change, significantly affecting ecosystems, public health, economic stability, and the global environmental balance. Major corporations are thus increasingly expected to adopt policies aimed at minimising these adverse impacts. For publicly traded companies, this may influence financial metrics such as earnings per share (EPS). Recent regulatory changes have required many Polish companies to disclose Environmental, Social and Governance (ESG) metrics, particularly for 2023. This represents a historic shift, although implementation delays have led many companies to report some metrics on a voluntary basis. The relationship between air pollution indicators – including the percentage of fossil fuel-derived energy, GHG intensity, and overall GHG footprint – and EPS can now be assessed within the Pope-Wang analytical framework. Early findings indicate a negative, though statistically insignificant, relationship between emissions and current EPS, as confirmed by Huber regression and quantile regression results. This suggests that emission-reduction measures have not yet had a substantial impact on the profitability of Warsaw Stock Exchange-listed companies that voluntarily reported ESG data.

Streszczenie

Ograniczenie emisji dwutlenku węgla (CO2) oraz innych gazów cieplarnianych (GHG) ma kluczowe znaczenie ze względu na ich zdolność do zatrzymywania ciepła w atmosferze, co prowadzi do wzrostu globalnej temperatury, powszechnie określanego jako globalne ocieplenie. Wzrost temperatury przyczynia się do zmian klimatycznych, które istotnie oddziałują na ekosystemy, zdrowie publiczne, stabilność gospodarczą oraz równowagę środowiska naturalnego na świecie. W związku z tym od dużych przedsiębiorstw coraz częściej oczekuje się wdrażania polityk mających na celu ograniczenie tych negatywnych skutków, co w przypadku spółek publicznych może wpływać na takie wskaźniki jak zysk na akcję (EPS). Nowe regulacje zobowiązały wiele polskich przedsiębiorstw do ujawniania wskaźników środowiskowych, społecznych i ładu korporacyjnego (ESG), w szczególności za rok 2023. Stanowi to historyczną zmianę, jednak opóźnienia wdrożeniowe sprawiły, że część spółek raportowała wybrane wskaźniki dobrowolnie. Zależność pomiędzy wskaźnikami zanieczyszczenia powietrza – w tym udziałem energii pochodzącej z paliw kopalnych, intensywnością emisji GHG oraz całkowitym śladem emisji gazów cieplarnianych – a EPS może być obecnie analizowana w ramach podejścia analitycznego Pope-Wanga. Wstępne wyniki wskazują na ujemną, lecz statystycznie nieistotną zależność pomiędzy emisjami a bieżącym EPS. Rezultat ten potwierdzają estymacje uzyskane przy zastosowaniu regresji Hubera oraz regresji kwantylowej. Otrzymane wyniki sugerują, że działania ukierunkowane na redukcję emisji nie miały jeszcze istotnego wpływu na rentowność spółek notowanych na Giełdzie Papierów Wartościowych w Warszawie, które dobrowolnie raportowały analizowane dane.

Słowa kluczowe:
GHG, paliwa kopalne, Giełda Papierów Wartościowych w Warszawie, gazy cieplarniane, zysk na akcję (EPS)

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Introduction

Environmental preservation is crucial to sustaining human life, as it safeguards essential resources, public health, and the ecosystems supporting all forms of life. While implementing such policies incurs considerable costs for businesses, they are essential. Compliance should also be evident among the top publicly traded companies on the Warsaw Stock Exchange, where the relationship between air pollution across their value chains and profit levels is measurable.

An extensive body of research investigates the link between corporate emissions and stock returns or valuation multiples, yet little analysis exists on the direct relationship between earnings per share (EPS) as well as rates of return and air pollution metrics. This study aims to bridge this gap, focusing specifically on the Warsaw Stock Exchange. In 2023, new regulatory requirements initially mandated listed companies to disclose comprehensive ESG data, including metrics on greenhouse gas emissions. However, implementation was deferred by one year, leading some companies to disclose their 2023 environmental statistics voluntarily.

With data supplied by Notoria S. A., the study uses regression models to examine whether CO_2 emissions, greenhouse gas intensity and related environmental metrics correlate with company profits in a statistically significant manner. Evidence of such a correlation would suggest that companies with a genuine commitment to environmental responsibility may reflect this through financial metrics such as EPS.

Literature review

Ideally, the monetary cost of carbon emissions would align with the comprehensive social cost, encompassing the full spectrum of climate impacts. Economic theories on climate, following the foundational work of **Nordhaus** [**1991**], conceptualise this as a global public goods dilemma that necessitates a worldwide Pigouvian carbon tax. Such a tax, equal to the social cost of carbon, aims to address this externality efficiently. Here, the social cost of carbon represents the cumulative, discounted projection of anticipated physical damages from climate change, resulting from the atmospheric buildup of carbon particles.

In experimental research, **Kuhn and Ulter** [**2019**] explored the psychological factors behind carbon offset purchasing, revealing that demand remains stable at lower price points, though individual behaviour varies significantly. For example, those with a high personal-responsibility index adjust their purchases based on personal, rather than collective, damage levels. **Görgen et al.** [**2020**] have further advanced this understanding by establishing a "carbon risk factor" and calculating a "carbon beta" specific to firms.

Technological solutions to reduce carbon and greenhouse gas (GHG) footprints are extensively studied across industries. While most studies focus on sector-specific methods, some propose comprehensive frameworks for addressing these emissions. **Choudhary et al.** [**2015**], for instance, introduced an optimisation model that incorporates carbon emission impacts into operational decisions such as facility layout in integrated logistics. John et al. [2021] presented a methodology that identifies CO_2 reduction opportunities and strategies for existing industrial sites, with the feasibility of carbon capture systems linked to reductions in raw material expenses and the availability of carbon tax relief. In further research, John [2022] expanded this framework by outlining an alternative, structured approach to carbon reduction planning, specifically for high-emission industrial sites.

Environmental protection policies introduce an additional layer of risk for companies, especially for those less committed to sustainable practices. Companies lagging in environmental sustainability are increasingly likely to encounter fines and regulatory costs as environmental legislation tightens worldwide. Consequently, investors are particularly attentive to how these risks might influence returns on their investments. Given this context, it is anticipated that risks associated with carbon emissions could impact share returns and valuations. An emerging area of study investigates the relationship between greenhouse gas emissions, including carbon dioxide, and stock pricing or returns for publicly traded firms.

The results of such research are varied. Heinkel, Kraus, and Zechner [2001] showed that when investors divest from high-emission companies, the stock returns of those firms tend to increase in the future. Conversely, Matsumura et al. [2013] found that high emissions are correlated with lower firm value, but that transparent voluntary emissions disclosures can reduce this negative effect. Hsu, Li, and Tsou [2019] observed that firms with higher pollution levels are more vulnerable to environmental regulation, resulting in higher average returns to offset this risk exposure. In a more specific study, Dzomonda and Fatoki [2020] analysed the Johannesburg Stock Exchange, finding that emissions reduction initiatives had a significant positive correlation with earnings per share and share price, implying a premium for companies committed to environmental compliance.

Bolton and Kacperczyk [2020] conducted a comprehensive study on the impact of carbon emissions on stock returns across US firms, finding that firms with higher emissions experienced higher returns, though they did not find a "carbon premium" related to emission intensity (carbon per revenue). They extended this research in 2022, showing that firms reducing emissions saw a modest increase in price-to-earnings ratios, with the extent of the premium varying by sector and company size. Their 2023 study across global markets found consistent evidence of higher returns for companies with high carbon emissions, attributing the carbon premium to market pricing of risk, which incentivises investors with higher returns in exchange for bearing additional risk. They also found that this premium exists across all sectors and continents studied. The study by Atilgan et al. [2023] finds that the "carbon premium" partially represents unexpected outperformance rather than priced risk, as companies with higher emissions enjoy superior earnings surprises and higher earnings announcement returns.

Conversely, other researchers have challenged the concept of a carbon premium. Aswani et al. [2021] reanalysed these findings, suggesting that the correlations between emissions and returns reported in previous studies were primarily due to unscaled, estimated emissions data rather than actual disclosed emissions. They found no significant relationship between emissions intensity and stock returns. This assertion was contested by Bolton and Kacperczyk [2023b], who contended that the fossil ratio is an inadequate measure of the influence of green factors on stock returns, and emphasised that absolute emission levels carry greater significance than the proportion of green activities relative to total operations. However, Aswani et al. [2023], disagreed with this finding. Additional studies by Cheema-Fox et al. [2021] supported Aswani's conclusions, noting that emissions intensity does not correlate with returns.

The recent outperformance of green assets has been attributed to heightened awareness of climate-related risks and evolving investor preferences, which have collectively driven up the prices of such assets while simultaneously reducing their expected returns [Pástor et al., 2022]. Based on this framework and empirical evidence, green assets were anticipated to deliver lower expected returns, both as a consequence of non-pecuniary preferences and due to their role as a hedge against climate risk. Salehi et al. [2022] observed that emissions negatively affected stock returns in the Iranian automotive industry, with emissions reductions linked to better performance.

Giglio et al. [2025] found that retail investors generally expected ESG investments to underperform the market, with substantial heterogeneity in both return expectations and investment motivations. The study also revealed that actual ESG investment behaviour correlated with investors' stated motivations (ethical, hedging or financial) as well as with their return expectations – with meaningful ESG holdings primarily among investors who expected these investments to outperform the market, including those whose primary motivations are ethical or hedging considerations.

Interestingly, the working paper by Stroebel and Wurgler [2021] surveyed 861 finance academics, professionals, and policy economists about climate finance topics. The respondents generally believed that regulatory risk was the top climate risk to businesses over the next five years while physical risks were the greatest concern over the next 30 years, and they overwhelmingly agreed that asset prices currently underestimate climate risks.

These findings illustrate ongoing debates about the impact of carbon emissions on financial performance and market returns, with differing conclusions shaped by variations in data sources, geographic focus, and methodological approaches.

The legal and reporting frameworks

The framework for mandatory environmental, social, and governance (ESG) reporting in the European Union was initially established with the Non-Financial Reporting Directive (NFRD), effective from October 2014 under Directive 2014/95/EU. This directive was significantly strengthened and broadened by the Corporate Sustainability Reporting Directive (CSRD), which was adopted in November 2022 as Directive (EU) 2022/2464. The CSRD expanded the scope of companies required to report ESG information and introduced stricter reporting standards. Since 2024, large public-interest entities have been required to adhere to the European Sustainability Reporting Standards (ESRS), which set standardised guidelines for reporting on a range of sustainability topics, including climate change, human rights, and governance. This ensures comparability and consistency across the EU. Developed by the European Financial Reporting Advisory Group (EFRAG), the ESRS were officially adopted by the European Commission in July 2023, with the CSRD rollout based on firm size and type starting in 2024. Implementation for companies listed on the Warsaw Stock Exchange was extended until January 2025 by Poland's Financial Supervision Authority (KNF), providing firms with additional time to prepare. As a result, in 2024, only some companies voluntarily reported limited data for the 2023 fiscal year.

The Greenhouse Gas (GHG) Protocol serves as a key framework for measuring and reporting greenhouse gas emissions globally. Created by the World Resources Institute and the World Business Council for Sustainable Development in the late 1990 s, it offers a standardised method for emissions management to improve transparency and accountability. The GHG footprint measures all greenhouse gases (CO_2, CH_4, N_2O, HFCs, etc.) produced directly and indirectly by an entity over a specific period. The impact of these gases is expressed in terms of $MgCO_2e$ (metric tonnes of carbon dioxide equivalents) to account for their varied effects on global warming. This footprint is central to ESG standards and helps organisations identify where to reduce emissions for sustainability.

Emissions are categorised by the GHG Protocol into three scopes: Scope 1 (direct emissions from sources directly controlled by a company), Scope 2 (indirect emissions from purchased energy), and Scope 3 (other indirect emissions across a company's value chain). Scope 3, the most complex to manage, includes emissions from sources not directly owned, such as suppliers and downstream activities. Companies may calculate Scope 2 emissions using either a market-based approach (based on specific energy sourcing contracts) or a location-based approach (based on average emissions for the grid where energy consumption occurs). Both calculation methods contribute to transparency in emissions reporting. The sum of GHG emissions from Scopes 1, 2, and 3 is called the GHG footprint.

Data

Data from Notoria S.A. indicates that 138 companies reported environmental, social, and governance (ESG) data in 2023. Among these, 82 disclosed the *2023_ec_fossil_ratio* (used by researchers including **Aswani et al. [2023]**) representing the percentage of total energy from fossil fuels, while 73 reported on *2023_ghg_footprint*. The breakdown of this data is presented in the accompanying table.

Table 1. Descriptive statistics

	2023_EPS	2022_BVPS	2022_P	2023_ec_ fossil_ratio	2023_ghg_ intensity	2023_ghg_ footprint	r_p	r_WIG
count	138	138	138	82	73	73	138	138
mean	13,46	68,02	137,88	0,72	130,50	2689538,00	0,41%	0,38%
std	75,31	200,89	908,90	0,36	304,41	11545480,00	1,20%	1,13%
min	-28,45	-1,05	0,79	0,00	0,21	599,00	−0,23%	−0,16%
max	866,27	2149,67	10650,00	1,00	1977,20	84627920,00	0,74%	0,61%

Source: Author's own calculations based on data from Notoria S.A.

The first two columns display financial data: earnings per share (EPS) at year-end 2023 and book value per share (BVPS) at year-end 2022. The *2023_ec_fossil_ratio* measures the percentage of fossil-fuel-based energy as a share of total energy consumption.

$$2023\_ec\_fossil\_ratio = \frac{2023\_fossil\_energy}{2023\_total\_energy}\left[\frac{MWh}{MWh}\right] \tag{1}$$

2023_ghg_intensity is calculated based on carbon footprint data (*2023_ghg_footprint*) in $MgCO_2e$, derived in a "liberal" way as the minimum of market-based (*ghg_footprint_mb*) and location-based (*ghg_footprint_lb*) emissions for companies that disclose either or both. Net sales for 2023 are specified in millions of PLN. For production companies, net sales reflect their total sales figures, while for banks, they are based on the banking operating result, and for insurance firms, they correspond to the insurance operating result.

$$2023\_ghg\_intensity = \frac{2023\_ghg\_footprint}{2023\_Net\_Sales}\left[\frac{MgCO2e}{mln\ PLN}\right] \tag{2}$$

To standardise these variables for regression analysis, each independent variable is linearly transformed to a scale between 0 and 1 using a MinMax scaler, facilitating comparability of the regression coefficients.

$$X_{transformed} = (X - X_{\min})/(X_{\max} - X_{\min}) \tag{3}$$

Additionally, daily rates of return are presented for individual stocks (*r_p*) as well as for the WIG market index (*r_WIG_p*) on the days when annual financial reports are published.

Methodology

The linear regression model used here predicts 2023 earnings per share (EPS) by applying ordinary least squares (OLS) estimation, with transformed independent variables including stock price (*2022_P*) and book value per share (*2022_BVPS*) at the end of 2022. The selection is based on the analytical framework introduced by **Pope and Wang [2005, 2014]**, which derives a theoretical relationship between book value, stock price, and earnings per share under the assumptions of linear valuation, no-arbitrage conditions, dividend irrelevance, and clean surplus accounting. Empirical evaluations conducted by **Harris and Wang [2019]** demonstrated that this model exhibits lower estimation bias and superior accuracy compared to other multivariate methods.

An additional analysis was conducted, focusing on stock price behaviour surrounding the publication dates of ESG reports. ESG disclosures are typically included in the Management Board's Report on Operations (MBRO), which accompanies the annual financial statements. Given that financial results for the preceding year are often partially disclosed through earlier quarterly reports, market reactions during the release period of yearly information may reflect new information beyond the financial figures alone – particularly ESG-related content. The Capital Asset Pricing Model – CAPM [**Sharpe, 1964**] serves as the basis for regressing the daily stock return on the publication date of an MBRO report r_p against the corresponding daily return of the WIG index, *r_WIG_p*. Within this analytical framework, the influence of environmental factors is examined.

To test for homoscedasticity, Breusch-Pagan and White tests are applied. Should these tests indicate heteroscedasticity, inefficiencies in estimators emerge despite retaining their unbiased nature. One remedy for this is the use of Heteroscedasticity-Consistent Standard Errors (HCSE), where estimations retain consistency by adjusting standard errors, confidence intervals, and p-values while keeping coefficient values unchanged. White's adjusted standard errors, specifically designed for these conditions, allow for more robust hypothesis testing by ensuring valid inference under heteroscedasticity. Both t-statistics and F-statistics are computed with these adjusted errors, thus compensating for potential heteroscedasticity or clustering in residuals.

To verify the normality of residuals, the Shapiro-Wilk and Jarque-Bera tests are performed. If the normality assumption does not hold, OLS estimators remain unbiased, consistent, and efficient as long as other assumptions are met. However, normality becomes essential for interpreting p-values and confidence intervals, particularly in smaller samples, since large deviations from normality affect the accuracy of statistics. According to the Central Limit Theorem (CLT), as sample size increases, the distribution of OLS estimates approximates normality, mitigating non-normality issues in larger samples. In small samples, normality remains crucial for inference validity.

In this context, there is no strict threshold defining a "large" sample, though CLT indicates that samples of 30 or more typically suffice for normality in the sampling distribution of the mean. A heuristic for regression is that the sample size n should exceed $50 + 8\ m$ (where m is the number of predictors) or even reach 100–200 for greater inference reliability. In this study, with slightly over 60 observations, additional methods such as Huber regression (HR) and quantile regression (QR) are applied to confirm OLS results with HCSE.

Huber regression, introduced by **Huber** [**1973**, **1981**], combines the OLS and LAD approaches, minimising a loss function that adjusts sensitivity to outliers by handling small residuals quadratically and large residuals linearly. This method is suited for moderate OLS assumption violations, balancing robustness and efficiency. Quantile regression, based on **Koenker and Hallock** [**2001**], offers insights into various conditional quantiles of the dependent variable, useful in cases of non-constant variance or non-normal errors. Quantile regression applied only for median quantile regression is primarily employed as a robustness check due to non-normality and the presence of outliers, rather than for the purpose of examining distributional effects. Moreover, the decision to report results solely for the median quantile stems from the limited sample size, which would render estimates for extreme quantiles unreliable.

Results and discussion

The regression results (Models 1–4) reported in Table 2 use EPS [2023] as the dependent variable, analysed against the explanatory variables of book value per share (*2022_BVPS*) and price (*2022_P*) for 2022, following the theoretical constructs from Pope and Wang, alongside environmental variables: the fossil fuel usage ratio (*2023_ec_fossil_ratio*), GHG intensity (*2023_ghg_intensity*), and GHG footprint (*2023_ghg_footprint*) for 2023. To address potential criticism that price – being a market rather than an accounting variable – might discount future pollution, Models 5–8 with book value per share in 2022 (*2022_BVPS*) were estimated. The *2022_P* variable was excluded from Models 5–8 because it is a market value, not an accounting value, and as such may discount information on ESG factors. This makes it possible to prevent information redundancy with technical variables. All regressions are estimated through OLS using heteroscedasticity-consistent standard errors (HCSE) to address heteroscedasticity identified by the Breusch-Pagan and White tests. The coefficient estimates align with the Pope and Wang frameworks, and all control variables are statistically significant. The coefficients on the pollution variables are negative in Models 1–4 and positive in Models 5–8; however, statistical significance is observed only in Model 4.

Table 2. The results of EPS regression estimated by OLS regression with HCSE

OLS (HCSE)	Model 1		Model 2		Model 3		Model 4	
	coef	t test p-value	coef	t test p-value	coef	t test p-value	coef	t test p-value
const	0,89	0,33	1,19	0,29	1,68	0,17	1,50	0,18
2022_BVPS	71,28	0,18	29,42	0,03	85,02	0,284	85,99	0,28
2022_P	798,91	0,00	36,28	0,01	748,39	0,00	783,41	0,00
2023_ec_fossil_ratio			–1,30	0,47				
2023_ghg_intensity					–5,25	0,23		
2023_ghg_footprint							–5,64	0,04
n	138		82		73		73	
Adj. R2	0,97		0,67		0,98		0,98	
F test p-value	0,00		0,00		0,00		0,00	
Breuche-Pagan test p-value	0,02		0,00		0,20		0,22	
White test p-value	0,00		0,00		0,00		0,00	
Shapiro-Wilk test p-value	0,00		0,00		0,00		0,00	
Jarque-Bera test p-value	0,00		0,00		0,00		0,00	
OLS (HCSE)	Model 5		Model 6		Model 7		Model 8	
	coef	t test p-value	coef	t test p-value	coef	t test p-value	coef	t test p-value
const	–10,38	0,00	0,87	0,51	–13,04	0,00	–12,72	0,00
2022_BVPS	742,49	0,00	54,53	0,00	827,97	0,00	827,83	0,00
2022_P								
2023_ec_fossil_ratio			0,16	0,94				
2023_ghg_intensity					5,01	0,57		
2023_ghg_footprint							0,86	0,87
n	138		82		73		73	
Adj. R2	0,85		0,57		0,93		0,93	
F test p-value	0,00		0,00		0,00		0,00	
Breuche-Pagan test p-value	0,00		0,00		0,01		0,01	
White test p-value	0,00		0,00		0,00		0,00	
Shapiro-Wilk test p-value	0,00		0,00		0,00		0,00	
Jarque-Bera test p-value	0,00		0,00		0,00		0,00	

Source: Author's own calculations based on data from Notoria S.A.

Models 9–12 demonstrate conformity with the Capital Asset Pricing Model, and the regressions reported in Table 3 indicate that all control variables behave similarly to those in Models 1–4, with corresponding coefficients remaining negative and statistically insignificant.

Normality tests using Shapiro-Wilk and Jarque-Bera indicate high kurtosis and skewness, leading to the estimation of Huber and quantile regressions for more reliable inference. Additionally, Models 2 and 6 show a significant decrease in adjusted R2, with notable coefficient shifts, possibly due to a unique subsample. In the Huber regression results in Tables 4 and 5, the coefficients conform to expectations under the Pope-Wang model, with pollution-related variables showing negative but statistically insignificant coefficients in all regressions. Given the limited sample size, quantile regression results in Tables 6 and 7 corroborate these findings. Thus, conclusions can be drawn about the negative value of coefficients related to pollution variables and their statistical significance.

Table 3. Rates of return estimated using OLS regression with HCE

OLS(HCSE)	Model 9		Model 10		Model 11		Model 12	
	coef	t test p-value	coef	t test p-value	coef	t test p-value	coef	t test p-value
const	0,06	0,26	0,10	0,35	0,12	0,29	0,18	0,21
r_WIG_p	1,13	0,03	1,07	0,05	1,15	0,41	1,06	0,02
2023_ec_fossil_ratio			–2,10	0,38				
2023_ghg_intensity					-4,21	0,33		
2023_ghg_footprint							–4,92	0,27
n	138		82		73		73	
Adj. R2	0,79		0,82		0,84		0,79	
F test p-value	0,00		0,00		0,00		0,00	
Breuche-Pagan test p-value	0,01		0,00		0,00		0,00	
White test p-value	0,00		0,00		0,00		0,00	
Shapiro-Wilk test p-value	0,00		0,00		0,00		0,00	
Jarque-Bera test p-value	0,00		0,00		0,00		0,00	

Source: Author's own calculations based on data from Notoria S.A.

Table 4. The results of EPS regression estimated using Huber regression

Huber Regression	Model 1		Model 2		Model 3		Model 4	
	coef	t test p-value	coef	t test p-value	coef	t test p-value	coef	t test p-value
const	0,023	0,94	0,48	0,48	0,04	0,93	0,07	0,87
2022_BVPS	83,611	0,00	29,18	0,00	86,78	0,00	86,33	0,00
2022_P	782,834	0,00	36,24	0,00	779,72	0,00	780,12	0,00
2023_ec_fossil_ratio			-0,43	0,61				
2023_ghg_intensity					–1,50	0,52		
2023_ghg_footprint							-3,61	0,13
n	138		82		73		73	
Adj. R2	0,97		0,66		0,97		0,98	
Huber Regression	Model 5		Model 6		Model 7		Model 8	
	coef	t test p-value	coef	t test p-value	coef	t test p-value	coef	t test p-value
const	–1,14	0,00	0,86	0,21	–5,63	0,00	–5,10	0,00
2022_BVPS	381,40	0,00	54,64	0,00	721,52	0,00	708,96	0,00
2022_P								
2023_ec_fossil_ratio			-0,46	0,58				
2023_ghg_intensity					-1,51	0,81		
2023_ghg_footprint							-5,57	0,38
n	138		82		73		73	
Adj. R2	0,65		0,55		0,92		0,91	

Source: Author's own calculations based on data from Notoria S.A.

Table 5. Rates of return estimated using Huber regression

Huber Regression	Model 9		Model 10		Model 11		Model 12	
	coef	t test p-value	coef	t test p-value	coef	t test p-value	coef	t test p-value
const	0,04	0,26	0,07	0,35	0,09	0,29	0,13	0,21
r_WIG_p	1,19	0,00	1,15	0,00	1,22	0,00	1,09	0,00
2023_ec_fossil_ratio			–1,10	0,58				
2023_ghg_intensity					-2,53	0,53		
2023_ghg_footprint							-3,01	0,49
n	138		82		73		73	
Adj. R2	0,79		0,81		0,83		0,79	

Source: Author's own calculations based on data from Notoria S.A.

Table 6. The results of EPS regression estimated using quantile regression

Quantile Regression	Model 1		Model 2		Model 3		Model 4	
	coef	t test p-value	coef	t test p-value	coef	t test p-value	coef	t test p-value
const	0,04	0,87	0,26	0,48	0,11	0,83	0,10	0,81
2022_BVPS	82,23	0,00	31,34	0,00	82,25	0,00	82,20	0,00
2022_P	784,00	0,00	38,25	0,00	783,98	0,00	784,08	0,00
2023_ec_fossil_ratio			–0,15	0,61				
2023_ghg_intensity					–0,83	0,74		
2023_ghg_footprint							–3,68	0,13
n	138		82		73		73	
Adj. R2	0,97		0,66		0,97		0,98	
Quantile Regression	Model 5		Model 6		Model 7		Model 8	
	coef	t test p-value	coef	t test p-value	coef	t test p-value	coef	t test p-value
const	–0,69	0,04	0,79	0,25	–2,61	0,04	–2,60	0,02
2022_BVPS	384,23	0,00	54,20	0,00	678,01	0,00	677,95	0,00
2022_P								
2023_ec_fossil_ratio			–0,68	0,40				
2023_ghg_intensity					–0,60	0,93		
2023_ghg_footprint							–7,48	0,30
n	138		82		73		73	
Adj. R2	0,65		0,55		0,90		0,90	

Source: Author's own calculations based on data from Notoria S.A.

Table 7. Rates of return estimated using quantile regression

Quantile Regression	Model 9		Model 10		Model 11		Model 12	
	coef	t test p-value	coef	t test p-value	coef	t test p-value	coef	t test p-value
const	0,05	0,34	0,10	0,42	0,12	0,39	0,13	0,30
r_WIG_p	1,16	0,00	1,11	0,00	1,18	0,00	1,10	0,00
2023_ec_fossil_ratio			–0,81	0,69				
2023_ghg_intensity					–1,73	0,66		
2023_ghg_footprint							–2,19	0,56
n	138		82		73		73	
Adj. R2	0,79		0,81		0,83		0,79	

Source: Author's own calculations based on data from Notoria S.A.

For all air pollution indicators – i.e. the fossil fuel usage ratio (*2023_ec_fossil_ratio*), GHG intensity (*2023_ghg_intensity*), and GHG footprint (*2023_ghg_footprint*) – the negative coefficients, while not statistically significant, imply a potential adverse association with current EPS. A similar pattern is observed for rates of return. This aligns with the theoretical assumptions that higher pollution may correlate with reduced EPS and lower rates of return, indicating possible environmental risk implications for corporate earnings. The lack of statistical significance suggests that pollution reduction costs may not yet substantially impact profits among Warsaw Stock Exchange – listed companies that report ESG metrics. It may also indicate an early stage of market transition in which environmental costs and benefits are beginning to be reflected in corporate performance but have not yet reached statistical significance. Hence, many such firms show limited commitment to environmental sustainability, investing minimally in eco-friendly policies, thereby obscuring any direct link between pollution levels and earnings. These observations partly mirror findings by **Aswani et al. [2021, 2023]** and **Cheema-Fox et al. [2021]**, suggesting no direct link between rates of return and emissions (since the rate of return depends on EPS).

Under the Corporate Sustainability Reporting Directive (CSRD), ESG disclosure was initially expected to become mandatory in 2023; however, implementation was postponed by one year. As a result, WSE-listed companies could choose whether to disclose ESG data in 2023. The voluntary nature of ESG data reporting creates potential selection bias, as companies that chose to disclose environmental metrics may differ systematically from those that did not. Companies with stronger environmental performance may be more willing to disclose their data, creating positive selection bias. Alternatively, companies anticipating future mandatory disclosure requirements might report early to demonstrate compliance readiness, regardless of their performance. Larger firms with more resources for ESG monitoring and reporting may also be overrepresented in the sample. These selection effects could partially explain why the study found negative but statistically insignificant relationships between emissions metrics and EPS. The voluntary nature of ESG reporting may have also resulted in a more homogeneous sample, potentially contributing to higher R^2 values. Consequently, the sample may not represent the full spectrum of companies listed on the Warsaw Stock Exchange, particularly those with worse environmental performance or different financial characteristics.

The paper adopts a "liberal" approach to calculating the greenhouse gas footprint by taking the minimum of market-based (*ghg_footprint_mb*) and location-based (*ghg_footprint_lb*) emissions for companies that disclose one or both. This approach was chosen to maximise the available sample size by including companies that reported using either methodology. However, this methodological choice may have potential important implications. By selecting the minimum value between market-based and location-based emissions, the approach systematically uses the lower emission figure for each company. This likely understates the true environmental impact across the sample. If emissions are consistently underreported in this way, the potential correlation between emissions and EPS may be attenuated. This could partially explain the negative but statistically insignificant relationships found in the study. Moreover, companies may strategically choose which methodology (market-based or location-based) presents their emissions more favourably. The "liberal" approach essentially allows companies to report their most favourable figure. Using the minimum value could compress the range of emission values in the dataset, potentially reducing statistical power to detect relationships with EPS.

Conclusions

Reducing reliance on fossil fuels is essential to limit climate change and curb global warming. Greenhouse gas (GHG) emissions degrade ecosystems, leading to habitat destruction, acid rain, ocean acidification, and loss of biodiversity. Policies aimed at minimising these environmental harms play a vital role in protecting both ecological and public health, contributing to a sustainable, resilient future. Global climate agreements, such as the Paris Agreement, emphasise the need for significant GHG reductions and limits on fossil fuel usage, highlighting the responsibility of large corporations, particularly publicly traded ones, to address these environmental impacts.

For the first time, many companies listed on the Warsaw Stock Exchange reported their 2023 environmental impact data, driven by new regulations requiring disclosure of ESG metrics, including GHG emissions. Although these requirements were delayed by one year, some companies chose to release this data voluntarily. This data allows for an analysis of the effects of fossil fuel reliance, GHG intensity, and overall emissions footprint on earnings per share (EPS), using the **Pope-Wang** framework [**2005**, **2014**], which incorporates book value per share and stock price as key explanatory variables.

The analysis reveals a negative relationship between GHG emissions, fossil fuel use, and EPS. However, this effect is statistically indistinguishable from zero. A similar pattern is observed for rates of return within the CAPM framework, as confirmed by both Huber and quantile regression results. This finding may indicate that pollution mitigation efforts have not yet been fully reflected in the earnings of Warsaw Stock Exchange – listed companies reporting ESG data. The result is broadly consistent with studies by **Aswani et al.** [**2021**, **2023**] and **Cheema-Fox et al.** [**2021**]. Future research could explore the impact of these environmental factors on other valuation metrics, such as the price-to-earnings (P/E) ratio, which, alongside EPS, influences stock prices.

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