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Modeling economic policy issues

Short-run and long-run effects of ESG policies on value creation and the cost of equity of firms

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ABSTRACT

Despite the general trend to include ESG scores in the evaluation of firm performance, the effect of ESG policies on the market value of companies is currently a subject of debate. In this paper we propose a dynamic version of Ohlson's model under time-varying discount rates consistent with the Campbell–Shiller present value identity. This enables differentiation between short term and long term implications of ESG performance on value creation, as well as income and substitution effects. Our results suggest that, although ESG policies imply almost no effects in the short-run, at longer horizons, better ESG performance results in lower value creation, mainly due to substitution effects channeled to market value via higher long-term discount rates. Our results are consistent with ESG strategies implying transitory effects on the cost of equity and the market value, which may result from time-varying investor preferences, long-term reputational penalties, or market misvaluation.

1. Introduction

Environmental issues, social policies and corporate governance concerns have experienced an extraordinary boom in recent years given their evident importance in a wide variety of areas, ranging from sustainable economics to politics. However, the effects of these aspects on corporate value creation are still far from clear. Furthermore, the classic distinction between short-run and long-run effects on the value of corporations and the cost of capital, typically analyzed in the literature on asset pricing and capital structure, is almost unexplored in the study of the impact of environmental, social and corporate governance (ESG) policies on firm performance. The fact that such considerations depend not only on the informational value of ESG policies on firm fundamentals, but also on investor preferences, largely explains the mixed results provided by the recent literature on the topic (Pedersen et al., 2021). Thus, while part of the literature concludes that ESG strategies are positively related to shareholder value (Hong and Kacperczyk, 2009; Luo and Balvers, 2017; Zerbib, 2020; Zhang and Lucey, 2022; Pástor et al., 2021, 2022), other studies conclude the opposite, stating that ESG policies translate into lower value creation (Hassel et al., 2005; Baker et al., 2018; Tampakoudis et al., 2021) or can produce ambiguous outcomes (Pedersen et al., 2021).

On this basis, in this paper we propose a dynamic Ohlson (1995) model, which uses *economic profit* to account for abnormal earnings under a time-varying cost of equity consistent with the Campbell and Shiller (1988) model, to study the

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extent to which the market value of stocks captures information resulting from the variation over time in ESG performance at the firm level. As shown below, according to our model, the contemporary cross-sectional relationship between ESG ratings and abnormal earnings, measured by economic profit, determines the short-run effects of ESG strategies on value creation, while the predictive power of the ESG score to forecast the components of economic profit – specifically return on equity (ROE) and cost of equity – captures long-run effects on the market value of shares. Therefore, based on the Ohlson (1995) model setup, we exploit these relationships to study the extent to which ESG policies imply short-term shocks and long-term effects on the value for shareholders.

We evaluate model performance using accounting and market data from all companies listed on the equity markets of the four largest economies in the euro zone, namely, Germany, France, Italy and Spain, for which Refinitiv® ESG Scores provided by the Datastream database are available. Remarkably, Refinitiv® provides data series that comprise one of the largest ESG data collection among private databases, collected from different sources of information such as annual reports, stock exchange filings, corporate social responsibility (CSR) reports or company websites. Thus, our final sample consists of five years of historical data from 2016 to 2020 for 487 firms, sorted into 'Banks', 'Industrial', 'Insurance' and 'Other financial' industries, following the general categories defined by Datastream. Hence, our sample not only allows us to study the effects of ESG strategies in aggregate terms, but also to analyze the differences that arise across different countries and sectors, and their relationship with different variables, such as the price-to-book value ratio, ROE and cost of capital.

Our paper contributes to the literature on the topic in the following terms. First, to the best of our knowledge, this is the first paper to use economic profit, determined according to a time-varying cost of equity consistent with Campbell and Shiller (1988), as a proxy for current abnormal earnings within the Ohlson (1995) model setup. In this regard, other literature in the area uses the Ohlson (1995) model to study the extent to which the market value of equities accounts for ESG information. For example, in their classic paper, Hassel et al. (2005) use the Ohlson (1995) model on Swedish listed firms to conclude that environmental performance has a negative influence on the market value of companies. However, to avoid an explicit specification of abnormal earnings, the authors reformulate the model to write market value increased by dividends paid in the period as a function of lagged market value and current net income. Landau et al. (2020) follow a similar approach to study the effect of integrated reports on the equity value of firms included in the STOXX Europe 50 index. However, both studies ignore the explicit definition of abnormal earnings and required rates of return in the model specification. In this context, we show below that our measure of economic profit is strongly significant and with high explanatory power for the difference between the market value and the book value of the companies under study.

Second, although previous research in the area analyzes the effect of ESG policies on value creation for specific sectors (Ionescu et al., 2019; Miralles-Quirós et al., 2019) or countries (Hassel et al., 2005; Bofinger et al., 2022; Rodríguez-García et al., 2022; Pástor et al., 2022), studies that simultaneously analyze the main industries and countries of the euro zone, both on an aggregate and an individual basis, are the exception. Furthermore, our database comprises 1846 observations, which represents a significantly larger sample than many studies on the topic. For example, Castro et al. (2021) use an approach based in part on the Ohlson (1995) model to study the impact of environmental performance on firms' stock prices. However, although the authors use a sample of 2638 European firms, their study covers only the effect of environmental variables on market value, ignoring social and governance issues. Similarly, Grassmann (2021) uses a sample of 8992 observations to study the effect of environmental expenditures and CSR on firm value. Importantly, our results show that the effects of ESG strategies on value creation exhibit different industry- and country-specific patterns, highlighting the relevance of our study and calling into question complete market integration at the European level.

Third, our approach allows us to distinguish short-run and long-run effects of ESG strategies on value creation, which has rarely been studied in the related literature despite its obvious importance. For example, the results documented by Hassel et al. (2005) allow the authors to conclude that the negative relationship between environmental performance and equity value suggests that the 'best' firms in terms of environmental policies are not, in general, highly valued by investors. However, the authors do not differentiate between short-term and long-term effects, thus overlooking potentially offsetting relationships in their research. Moreover, this shortcoming is present in most of the related literature (Ionescu et al., 2019; Landau et al., 2020; Castro et al., 2021; Grassmann, 2021). In contrast, the conditional nature of our model allows us to study the effects of ESG strategies on current ROE and cost of equity, but also their impact on long-term value creation. In fact, the conditional form in which our model is expressed represents an important advance in relation to other asset pricing models developed to account for ESG information. For example, Pástor et al. (2021) and Pástor et al. (2022) assume heterogeneous investor tastes for green holdings and a single-period setup to propose a two-factor model that accounts for the effects of ESG preferences on unconditional expected returns. However, the unconditional nature of the model developed by the authors hinders a straight evaluation of the effects of ESG policies over time.

Our results show that while in some industries ESG policies enhance value creation, in most cases a higher ESG commitment translates into lower long-term market value relative to book value. Furthermore, with some exceptions, for most of the countries and sectors under analysis, this lower value creation is primarily driven by long-term effects inducing higher discount rates, which in the vast majority of cases is not compensated with a higher ROE. Hence, our results are consistent with ESG strategies translating into higher expected returns in the long-run rather than with negative effects on expected earnings due to costs incurred to improve environmental performance.

The remainder of the paper is organized as follows. Section 2 defines the model. Section 3 describes the data and discusses model results. Finally, Section 4 concludes the paper.

2. Methodology

We build on the classic Gordon dividend growth model and an accounting system that satisfies a clean surplus relation, as follows:

$$P_t = \sum_{\tau=1}^{\infty} R^{-\tau} E_t \left(D_{t+\tau}\right) \tag{1}$$

$$B_t = B_{t-1} + X_t - D_t \tag{2}$$

where P_t is the share price at time t, R is the required rate of return plus unity, $E_t(\cdot)$ is the expectation conditional on time t information, D_t is the dividend paid at time t, B_t is the book value per share, and X_t denotes earnings per share at time t, under the assumption that the company keeps the number of shares constant over time in order to simplify notation. In this framework, residual income valuation models arise naturally by defining abnormal earnings per share X_t^a as the difference between earnings and the expected return on equity:

$$X_t^a = X_t - (R-1)\, B_{t-1} \tag{3}$$

Hence, Eqs. (1) to (3) result in the following residual income valuation model:

$$P_t = B_t + \sum_{\tau=1}^{\infty} R^{-\tau} E_t \left(X_{t+\tau}^a\right) \tag{4}$$

Eq. (4) allows us to directly relate the Ohlson (1995) model and the Campbell and Shiller (1988) present value identity. In particular, the Ohlson (1995) model introduces specific information dynamics for abnormal earnings, as follows:

$$X_{t+1}^a = \omega X_t^a + \nu_t + \varepsilon_{t+1} \tag{5}$$

$$\nu_{t+1} = \gamma \nu_t + \eta_{t+1} \tag{6}$$

where ν_t denotes relevant information not captured by accounting, ω and γ are parameters, and ε_{t+1} and η_{t+1} are error terms. Based on Eqs. (4) to (6), Ohlson (1995) obtains the following pricing function:

$$P_t = B_t + \Phi_1 X_t^a + \Phi_2\, \nu_t \tag{7}$$

where:

$$\Phi_1 = \omega / \left(R - \omega\right) \tag{8}$$

$$\Phi_2 = R / \left[\left(R-\omega\right)\left(R-\gamma\right)\right] \tag{9}$$

Importantly, although Eqs. (8) and (9) show that Φ_1 and Φ_2 can be determined endogenously within the model setup, in practice these coefficients are often used as regression coefficients for model evaluation purposes. Furthermore, following the common practice of testing the Ohlson (1995) model using panel data analysis under fixed or variable effects, Φ_1 and Φ_2 are often assumed to be constant over time. However, this practice is inconsistent with the main results and conclusions of the literature on the predictability of stock returns, which shows that different economic and non-economic variables exhibit significant predictive power in forecasting expected returns (Campbell, 1987; Fama and French, 1988; Baker and Wurgler, 2000; Lettau and Ludvigson, 2001; Lamont and Stein, 2004; Cochrane, 2011; Novy-Marx, 2014; Rojo-Suárez et al., 2022). On this basis, Campbell and Shiller (1988) develop their widely-recognized loglinear present value model, which overcomes the constraint of a constant discount rate in Eq. (1) to account for evidence of stock return predictability. Hence, based on the standard definition of gross return:

$$R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t} \tag{10}$$

Campbell and Shiller (1988) derive the following present value identity:

$$pd_t \approx \sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j} - \sum_{j=1}^{\infty} \rho^{j-1} r_{t+j} \tag{11}$$

where pd_t is the price–dividend ratio in logs at time t, r_{t+j} is the log return, Δd_{t+j} is log dividend growth, and $\rho = \exp(pd) / [1 + \exp(pd)]$. We can use Eq. (11) instead of Eq. (1) to derive the Ohlson (1995) model without loss of generality, resulting in the following pricing function:

$$P_t = B_t + \Phi_{1,t}\left(\mathbf{R}\right) X_t^a + \Phi_{2,t}\left(\mathbf{R}\right) \nu_t \tag{12}$$

where $\Phi_{j,t}(\mathbf{R})$ denotes model coefficients at time t, conditional on the vector of expected returns $\mathbf{R}$. Remarkably, Eq. (12) shows that time-varying discount rates directly result in time-varying model coefficients, in which we call hereafter the dynamic Ohlson model. At this point, it is important to note that the predictability pattern of dividend growth and discount rates relies heavily on the forecasting regression of the two terms in the right-hand side of Eq. (11) on the variables used as predictors. Specifically, using the classic derivation of Campbell and Shiller (1988):

$$\sum_{j=1}^{\infty} \rho^{j-1} \Delta d_t = b_d dp_t + \varepsilon^d \tag{13}$$

$$\sum_{j=1}^{\infty} \rho^{j-1} r_{t+j} = b_r dp_t + \varepsilon^r \tag{14}$$

where dp_t is the dividend yield in logs, b_d and b_r are regression coefficients, and ε^d and ε^r are error terms. Furthermore, recent research on return predictability opens the door to multivariate explanations in forecasting dividends and expected returns, which implies that Eqs. (13) and (14) must consider forecasting variables other than the dividend yield to capture short-run and long-run effects on predictability patterns (Cochrane, 2011). Accordingly, the dynamics represented in Eqs. (11), (13) and (14) allow us to write abnormal earnings X_t^a in Eq. (12) as a function of the forecasting regressions of their main components. Specifically, scaling X_t^a by the opening book value, Eq. (3) naturally results in the following expressions:

$$X_{t+\tau}/B_t = \mathbf{b}_X' \mathbf{F}_t + \varepsilon_{t+\tau}^X \tag{15}$$

$$R_{t+\tau} = \mathbf{b}_R' \mathbf{F}_t + \varepsilon_{t+\tau}^R \tag{16}$$

where τ denotes the number of lags, $\mathbf{b}_X$ and $\mathbf{b}_R$ are K-dimensional vectors of parameters, $\mathbf{F}_t$ is a K-dimensional vector of predictors, and ε_t^X and ε_t^R are error terms.

In order to keep the model in Eqs. (12), (15) and (16) useful and manageable for practical applications, below we introduce the following transformations to analyze the effect of ESG policies on value creation and cost of capital. First, we use Eq. (12) to explain the difference between the market value and book value of shares over time instead of the market price. Second, we proxy abnormal earnings by economic profit, that is, the product of the opening book value and the difference between the ROE and the stock return. Third, we identify relevant information not yet captured by accounting ν_t in Eq. (12) and the vector of predictors $\mathbf{F}_t$ in Eqs. (15) and (16) with ESG performance captured by the variation in ESG scores. Accordingly, Eqs. (12), (15) and (16) can be rewritten as follows:

$$MV_{i,t+\tau} - BV_{i,t+\tau} = \Phi_t + \Phi_{EP,t} EP_{i,t} + \Phi_{ESG,t} \Delta ESG_{i,t} + \varepsilon_{i,t+\tau}^{MV-BV} \tag{17}$$

$$ROE_{i,t+\tau} = a^{ROE} + b_{ESG}^{ROE} \Delta ESG_{i,t} + \varepsilon_{i,t+\tau}^{ROE} \tag{18}$$

$$R_{i,t+\tau} = a^R + b_{RM}^R RM_{t+\tau} + b_{ESG}^R \Delta ESG_{i,t} + \varepsilon_{i,t+\tau}^R \tag{19}$$

where $MV_{i,t}$ denotes the market value of equity for the company i at time t, $BV_{i,t}$ is the book value of equity, $EP_{i,t}$ is the economic profit, $\Delta ESG_{i,t}$ is the variation rate of the ESG score, RM_t is the return on the market portfolio, the coefficients Φ, a and b are model parameters, and the variables ε are error terms. Consistent with the literature on stock return predictability, Eq. (17) shows that the t subscripts in Φ coefficients allow the model to account for time-varying expected returns, which means that the procedure used to estimate these parameters in Eq. (17) must be consistent with this fact.

Regarding Equation (19), consistent with the Campbell and Shiller (1988) present value identity, the returns $R_{i,t}$ are determined according to the standard definition of gross return in Eq. (10). Furthermore, these returns together with $ROE_{i,t}$ in Eq. (18) determine EP_i in Eq. (17), which illustrates the fact that Eqs. (17) to (19) are interrelated parts of the same model and, consequently, must be interpreted jointly. Finally, given the strong comovement of stocks in equity markets, in order to allow the model to isolate the fraction of returns that results from the variation of ESG scores, Eq. (19) includes the return on the market portfolio – that is, the return on a broad-based value-weighted portfolio – as an explanatory variable.

As noted, in the next section we use the defined model to analyze the effects of ESG strategies on value creation, ROE and cost of equity for all companies traded on the securities exchanges of the four largest economies of the euro zone, namely, Germany, France, Italy and Spain. In this context, our model not only allows us to isolate income and substitution effects through the study of $ROE_{i,t}$ and $R_{i,t}$ dynamics, respectively, but also provides a robust framework to evaluate the effects of ESG policies at different horizons.

3. Results and discussion

We compile all accounting and market data from the Datastream database. Specifically, we use the 'Worldscope Balance Sheet' and 'Worldscope Profit & Loss Statement' templates to compile the financial statements of all listed firms in the four largest economies in the euro zone by GDP for which Refinitiv® ESG Scores are available. This search totals 517 companies, of which 188 are German, 159 French, 99 Italian and 71 Spanish. However, the strong presence of missing

Table 1
Total number of observations.

Country	Sector	Number of observations
All	All	1846
All	Banks	108
All	Industrial	1526
All	Insurance	68
All	Other fin.	144
Germany	All	653
France	All	586
Italy	All	345
Spain	All	262

data for some companies and for the years prior to 2016 reduces our sample to 487 firms and an annual data time interval spanning 2016 to 2020. As noted above, we use the general categories defined by Datastream to sort all companies into four groups, namely, 'Banks', 'Industrial', 'Insurance' and 'Other financial' industries. Table 1 shows the total number of observations in our sample by industry and by country.

In order to determine stock returns and account for the market value of the firms under study, we compile total return and market value series from the Datastream database (RI and MV series, respectively). Importantly, total return series includes returns resulting from price variations as well as dividend payments, as required by the model. Additionally, we proxy the return on the market portfolio series by the cross-sectional average return of the companies under analysis, weighted by market value.

Regarding ESG indicators, we use Refinitiv® ESG Scores to proxy for $ESG_{i,t}$ in Eqs. (17) to (19). These indicators are divided into three groups, namely, the Environmental Score, the Social Score and the Governance Score, each including different data categories. Thus, the Environmental Score is divided into 'Resource use', 'Emission' and 'Environmental innovation' scores. The Social Score includes 'Workforce', 'Human rights' and 'Community' scores. Finally, the Governance Score consists of scores for 'Management', 'Shareholders' and 'CSR strategy'. Table A.1 in Appendix A shows full details on the variables used to determine these scores, some of which are numeric while others are Boolean. Therefore, the Environmental Score, the Social Score and the Governance Score result from determining weighted averages of these indicators, ranging from 0 to 100. Additionally, we estimate an integrated ESG score that is determined by the weighted average of the three scores provided by Refinitiv, hereinafter referred to as the ESG score.

Fig. 1 shows the means and confidence intervals for different variables, namely, price-to-book value ratios, ROE, cost of equity and ESG score. It should be noted that, although the ROE follows a downward trend over time for the period under study, the cost of equity reaches a minimum value in 2019 to increase considerably in 2020, probably due to the turbulence caused by the COVID-19 pandemic. For this time interval, the ESG score exhibits a U-shape with a minimum value in 2018. Regarding industries, the industrial sector is the one that presents the highest price-to-book value ratio and ROE among those considered, also exhibiting a high cost of equity. Conversely, banks and insurance companies have the lowest price-to-book value and ROE, with banks also having the lowest cost of equity and the highest ESG score. Focusing on country-specific patterns, Fig. 1 shows that Spain has the highest – albeit widely dispersed – price-to-book value ratio and ROE, as well as the highest ESG score. On the other hand, Germany exhibits the highest cost of equity and the lowest ESG score, as well as remarkably low ROE.

Regarding the estimation procedures followed to determine model coefficients, we use different panel data analysis tools to adapt model estimation to the specific features of Eqs. (17) to (19). Specifically, the time-varying coefficients in Eq. (17) require the use of panel data estimation under variable coefficients. By contrast, the constant coefficients in Eqs. (18) and (19) allow us to use standard panel data analysis to estimate their parameters. Additionally, according to the results provided by the Hausman test on the models under study, we assume fixed effects in the estimation of Eq. (17), while random effects to estimate parameters in Eqs. (18) and (19). Consequently, Tables 2 to 4 show the main results obtained for Eqs. (17) to (19), respectively, using the ESG score to account for ESG performance. In order to study short-run and long-run effects of ESG policies, each table shows the model results assuming 0 to 2 lags in the ESG score. Additionally, Table B.1 to Table B.9 in Appendix B show model results using the Environmental Score, the Social Score and the Governance Score as information variables instead of the ESG score.

Table 2 documents the estimates for the slope coefficients in Eq. (17), as well as the standard errors and R^2 statistics ignoring and including $\Delta ESG_{i,t}$ as information variable (labeled 'R^2 plain' and 'R^2 full' in Table 2, respectively), with the last column showing the difference between these R^2 statistics. The results in Table 2 provide us with several important findings. First, as noted, economic profit exhibits a strongly significant explanatory power for the difference between market value and book value, where in the vast majority of cases a higher contemporary economic profit translates into a lower value for $MV_{i,t} - BV_{i,t}$, and vice versa. Moreover, the significance of economic profit is particularly important in the case of the banking sector. Nevertheless, it should be noted that the negative relationship between economic profit and value creation is a logical consequence of the dynamics represented in Eqs. (10) and (17). Indeed, a higher economic profit at time t implies a higher value of $ROE_{i,t}$ relative to $R_{i,t}$, which, at least in period t, implies a stronger positive variation in book value than in market value *ceteris paribus*.

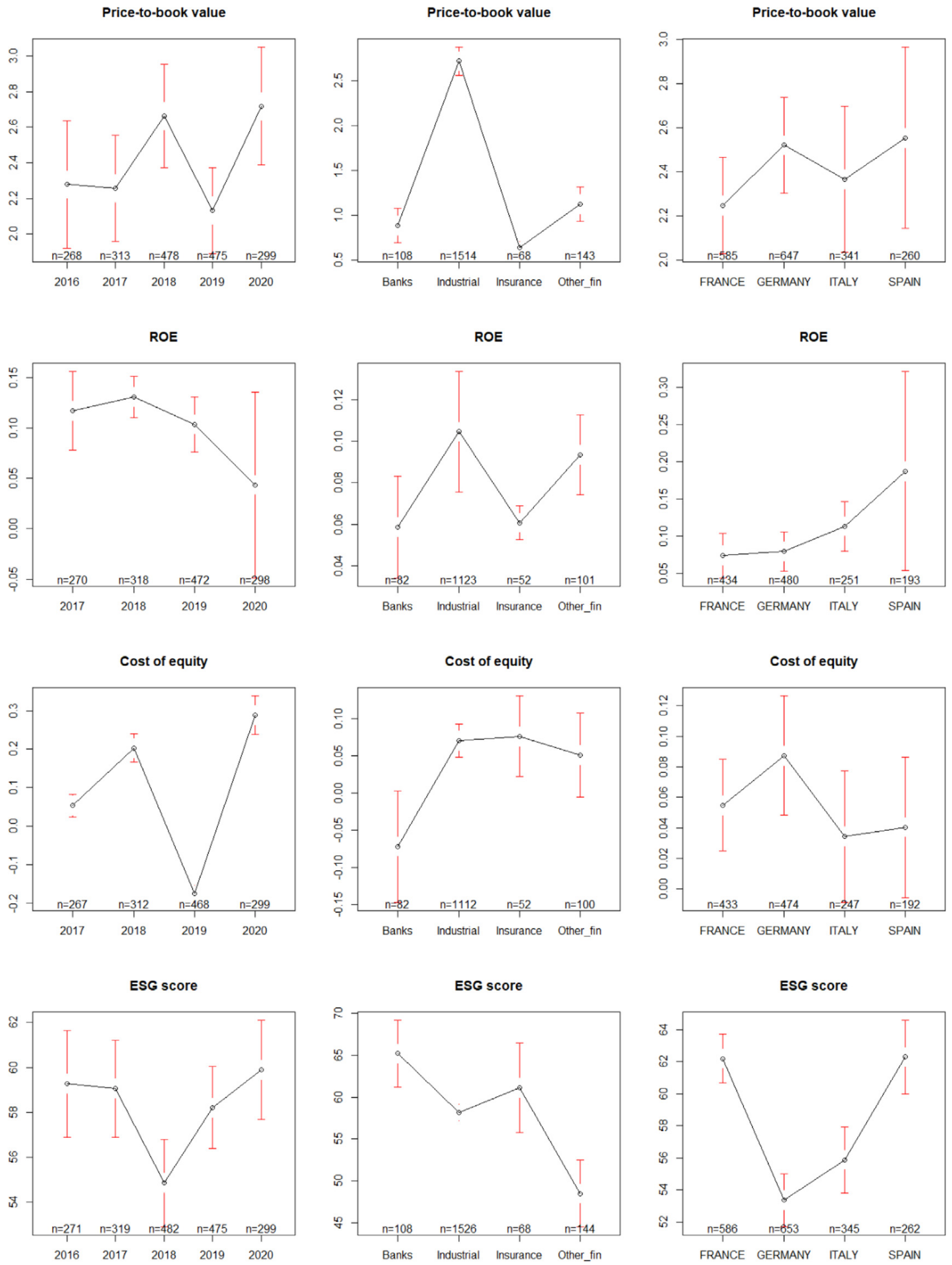

Fig. 1. Means and confidence intervals of the variables under analysis.

Second, Table 2 shows that the variation in the ESG score exhibits low explanatory power in Panels A and B, meaning that ESG policies seem to imply negligible effects in value creation in the short-run. In fact, only for the insurance sector in Panel A does the variation in the ESG score become statistically significant, implying in turn an increase in the R^2 statistic of 7.2%. However, Table 2 also shows that, at longer horizons, the variation in the ESG score becomes statistically

Table 2
Regression results for $MV_{i,t} - BV_{i,t}$ using the ESG score as information variable.

Country	Sector	Φ_{EP}	$\sigma(\Phi_{EP})$	$\Phi_{ESG}\cdot\ 10^{-3}$	$\sigma(\Phi_{ESG})\cdot\ 10^{-3}$	R^2 plain	R^2 full	Diff.
Panel A: Number of lags = 0								
All	All	−1.149***	0.117	−0.005	0.004	16.5%	17.4%	1.0%
All	Banks	−1.300***	0.066	0.016	0.013	83.2%	84.7%	1.5%
All	Industrial	−1.228***	0.310	−0.009	0.005	14.4%	16.8%	2.4%
All	Insurance	−2.063***	0.281	−0.114***	0.033	70.7%	78.0%	7.2%
All	Other fin.	−1.973***	0.272	0.006	0.008	51.4%	53.4%	2.1%
Germany	All	−0.948***	0.174	−0.016*	0.007	24.4%	26.7%	2.3%
France	All	−1.452***	0.255	−0.020	0.013	15.9%	17.5%	1.6%
Italy	All	−1.673***	0.177	0.001	0.003	43.8%	44.0%	0.2%
Spain	All	3.752***	0.854	−0.007	0.008	22.9%	24.2%	1.4%
Panel B: Number of lags = 1								
All	All	−1.259***	0.144	−0.006	0.004	16.5%	20.1%	3.6%
All	Banks	−1.298***	0.082	0.008	0.010	83.2%	90.4%	7.2%
All	Industrial	−1.183***	0.312	−0.008	0.005	14.4%	18.3%	3.8%
All	Insurance	−2.041***	0.301	0.009	0.014	70.7%	79.6%	8.9%
All	Other fin.	1.809***	0.318	0.002	0.004	51.4%	57.1%	5.7%
Germany	All	−1.044***	0.223	−0.011	0.007	24.4%	29.2%	4.8%
France	All	−1.622***	0.302	−0.023	0.016	15.9%	20.3%	4.3%
Italy	All	−1.479***	0.226	−0.002	0.003	43.8%	34.2%	−9.6%
Spain	All	3.810***	0.896	−0.006	0.008	22.9%	28.3%	5.4%
Panel C: Number of lags = 2								
All	All	−1.315***	0.155	−0.012**	0.004	16.5%	24.2%	7.7%
All	Banks	−1.324***	0.087	−0.005	0.005	83.2%	96.7%	13.5%
All	Industrial	−0.990*	0.390	−0.011*	0.005	14.4%	18.8%	4.4%
All	Insurance	−1.955***	0.318	0.009	0.010	70.7%	88.3%	17.6%
All	Other fin.	−2.124***	0.361	−0.009	0.006	51.4%	80.7%	29.4%
Germany	All	−1.132***	0.244	−0.012*	0.006	24.4%	33.3%	8.9%
France	All	−1.664***	0.316	−0.026	0.016	15.9%	25.3%	9.3%
Italy	All	−1.483***	0.259	−0.002	0.004	43.8%	39.9%	−3.9%
Spain	All	−0.962**	0.306	−0.013	0.020	22.9%	23.7%	0.9%

Note: The table shows the slope coefficients and standard errors that result from the panel data regression of the difference between the market value and the book value, using the ESG score as an information variable. Asterisks denote significance, where $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$. Each panel use a different number of lags for the ESG score, ranging from 0 to 2. Columns labeled 'R^2 plain' and 'R^2 full' show the R^2 statistics of the regressions ignoring or including the ESG score as an information variable, respectively. The column labeled 'Diff.' shows the difference between these statistics.

significant in the entire sample, implying important increases in the R^2 statistics in several cases, especially for companies in the financial sector (i.e. banks, insurance companies and other financial firms). Thus, while the 2-lag ESG score in Panel C results in the R^2 statistic for the banking sector increasing from 83.2% to 96.7%, for the insurance sector it increases from 70.7% to 88.3%. Furthermore, in the case of other financial companies, the R^2 statistic rises from 51.4% to 80.7%. Across the countries considered, the effects of firm-specific ESG policies are much smaller, with only Germany providing statistically significant coefficients, albeit a modest increase in the R^2 statistic.

As noted above, the coefficients Φ_{ESG} in Table 2 show that the variation in ESG score is, in general, inversely related to the difference between market value and book value, meaning that the greater the increase in ESG performance, the lower the value of $MV_{i,t} - BV_{i,t}$, and vice versa. In this regard, Eqs. (13) and (14), and their equivalents, Eqs. (18) and (19), show that, within our model setup, the variation in the ESG score influences $MV_{i,t} - BV_{i,t}$ via $ROE_{i,t}$ and $R_{i,t}$ at potentially infinite horizons. Accordingly, in order to study the effects of ESG policies on ROE and cost of equity at different horizons, Table 3 shows the regression results for Eq. (18), while Table 4 does the same for Eq. (19). Specifically, Table 3 shows the estimates for the slope coefficient, the p-value and the R^2 statistic that result from the forecasting regressions of the ROE on the variation in the ESG score (see Eq. (18)) across industries and countries. On the other hand, Table 4 has the same structure as Table 2, showing the estimates for the slope coefficients in Eq. (19), the p-values and the R^2 statistics ignoring and including $\Delta ESG_{i,t}$ as a predictor, with the last column showing the difference between both R^2 statistics.

The results in Table 3 show that ROE is scarcely affected by the variation in the ESG score at all horizons. Furthermore, this applies to all industries and countries under analysis, with the insurance sector in Panel C achieving the highest R^2 statistic (27.3%). These results suggest that, contrary to previous literature that refers to the cost-concerned school to explain the negative influence of environmental performance on the market value of firms (see for example Hassel et al. (2005) and Landau et al. (2020)), cost increases tied to ESG strategies do not seem to explain the lower value creation of companies with higher ESG scores. On the contrary, as illustrated in Tables 3 and 4, our results suggest that it is not the effects of ESG policies on ROE (i.e. income effects), but rather the effects on discount rates (i.e. substitution effects) that primarily drive differences in value creation across firms. Specifically, the results in Table 4 show that, although the variation in the ESG score has a small effect on the cost of equity in the short-run, its explanatory power increases significantly with the horizon, as it is the case with $MV_{i,t} - BV_{i,t}$ in Table 2.

Table 3
Regression results for $ROE_{i,t}$ using the ESG score as information variable.

Country	Sector	b_{ESG}^{ROE}	$p\left(b_{ESG}^{ROE}\right)$	R^2
Panel A: Number of lags = 0				
All	All	0.018	0.499	0.0%
All	Banks	0.067	0.147	2.4%
All	Industrial	0.018	0.534	0.0%
All	Insurance	−0.010	0.331	3.8%
All	Other fin.	0.008	0.765	0.8%
Germany	All	0.111**	0.041	0.9%
France	All	0.128	0.165	0.3%
Italy	All	0.077	0.233	0.7%
Spain	All	−0.005	0.936	0.0%
Panel B: Number of lags = 1				
All	All	0.002	0.947	0.0%
All	Banks	−0.002	0.960	0.4%
All	Industrial	0.002	0.958	0.0%
All	Insurance	0.013	0.183	9.7%
All	Other fin.	0.050	0.251	4.0%
Germany	All	0.029	0.615	0.2%
France	All	−0.227**	0.043	1.4%
Italy	All	0.053	0.363	0.3%
Spain	All	−0.003	0.967	0.0%
Panel C: Number of lags = 2				
All	All	−0.008	0.958	0.0%
All	Banks	0.085	0.272	1.6%
All	Industrial	−0.018	0.929	0.0%
All	Insurance	−0.005	0.769	27.3%
All	Other fin.	−0.015	0.846	4.0%
Germany	All	0.045	0.660	0.1%
France	All	−0.381*	0.082	1.9%
Italy	All	0.040	0.560	6.8%
Spain	All	0.221	0.840	0.1%

Note: The table shows the slope coefficient and the p-value that result from the panel data regression of ROE, using the ESG score as an information variable. Asterisks denote significance, where $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$. The table also provides the R^2 statistic of the regressions. Each panel use a different number of lags for the ESG score, ranging from 0 to 2.

More precisely, Table 4 shows that contemporary and 1-lag ESG scores are essentially useless in explaining the cross-sectional variation of discount rates (see Panels A and B), with only the banking sector experiencing a modest 10% increase in the R^2 statistic in Panel B. However, Panel C in Table 4 shows that the variation in the ESG score becomes highly explanatory when forecasting the cost of equity at a 2-year horizon, especially for companies in financial sectors. In particular, while $\Delta ESG_{i,t}$ causes the R^2 statistic for the banking sector to increase from 37.5% to 61.1%, the R^2 statistic for 'Other financial' firms rises from 41.2% to 66.5%. Regarding the countries under study, the variation in the R^2 statistic is highest for Germany and Spain, where $\Delta ESG_{i,t}$ leads the R^2 statistic to increase by 15.9% and 12.7%, respectively.

Importantly, in most of the cases represented in Table 4, Panel C, the slope coefficient b_{ESG}^{R} is positive, meaning that a higher ESG performance generally implies a higher discount rate in the long-run, and vice versa. This fact is notable for banks and 'Other financial' firms, for which the b_{ESG}^{R} coefficients are strongly significant. On the other hand, Table 4 also shows that the return on the market portfolio RM_t has significant explanatory power in estimating discount rates for most of the industries and countries under analysis, consistent with the strong comovement of stock returns. Furthermore, the b_{RM}^{R} coefficients can be interpreted within the capital asset pricing model setup (Sharpe, 1964; Lintner, 1965a,b) as the beta coefficients of stock returns on the wealth portfolio return, where Table 4 shows that for most of the industries and countries under study betas are around 1, with the exception of the insurance sector, where the beta coefficient is below 0.5.

Summarizing the results from Tables 2 to 4 we have the following. Although the effects of ESG policies are small and show little significance in the short-run, for longer time intervals, ESG performance is inversely related to the difference between the market value and the book value, and generally implies a higher cost of capital in the long-run for most of the sectors and countries under study. Conversely, the effects of the ESG strategies on ROE are almost negligible for all horizons. Remarkably, contemporary economic profit has a significant negative effect on value creation across all horizons.

Most of the patterns illustrated in Tables 2 to 4 persist in Table B.1 to B.9 in Appendix B, where we use the Environmental Score, Social Score and Governance Score instead of the ESG score as information variables. Remarkably, the Governance Score provides a statistically significant 2-year Φ_G coefficient using the entire sample (see Panel C in Table B.7), with values similar to those shown in Table 2 for the ESG score. In contrast, although the Environmental Score and Social Score in Tables B.1 and B.4 allow Equation (17) to increase the R^2 statistic to the same extent as the ESG score in

Table 4
Regression results for $R_{i,t}$ using the ESG score as information variable.

Country	Sector	b^R_{RM}	$p\left(b^R_{RM}\right)$	b^R_{ESG}	$p\left(b^R_{ESG}\right)$	R^2 plain	R^2 full	Diff.
Panel A: Number of lags = 0								
All	All	1.002***	0.000	0.024	0.182	27.8%	27.9%	0.1%
All	Banks	0.975***	0.000	−0.029	0.833	37.5%	37.7%	0.2%
All	Industrial	1.032***	0.000	0.029	0.131	27.5%	27.6%	0.2%
All	Insurance	0.424***	0.002	−0.118*	0.061	17.9%	23.4%	5.5%
All	Other fin.	0.978***	0.000	−0.074	0.410	41.2%	41.8%	0.6%
Germany	All	1.246***	0.000	0.133**	0.047	31.0%	31.5%	0.5%
France	All	0.918***	0.000	0.037	0.640	29.3%	29.3%	0.1%
Italy	All	0.981***	0.000	−0.167**	0.033	39.8%	41.4%	1.5%
Spain	All	0.582***	0.000	0.018	0.364	11.1%	11.5%	0.4%
Panel B: Number of lags = 1								
All	All	0.932***	0.000	−0.007	0.721	27.8%	27.0%	−0.8%
All	Banks	0.980***	0.000	−0.000	0.998	37.5%	47.5%	10.0%
All	Industrial	0.962***	0.000	−0.010	0.644	27.5%	26.4%	−1.1%
All	Insurance	0.381***	0.006	0.048	0.447	17.9%	20.8%	3.0%
All	Other fin.	0.839***	0.000	0.125	0.332	41.2%	37.5%	−3.7%
Germany	All	1.148***	0.000	0.075	0.418	31.0%	29.8%	−1.2%
France	All	0.838***	0.000	−0.055	0.595	29.3%	27.9%	−1.4%
Italy	All	0.890***	0.000	0.056	0.536	39.8%	38.1%	−1.8%
Spain	All	0.628***	0.000	−0.014	0.496	11.1%	14.5%	3.4%
Panel C: Number of lags = 2								
All	All	0.941***	0.000	0.080	0.246	27.8%	35.7%	8.0%
All	Banks	0.903***	0.000	0.553**	0.017	37.5%	61.1%	23.6%
All	Industrial	0.974***	0.000	0.003	0.976	27.5%	36.0%	8.6%
All	Insurance	0.406**	0.012	−0.136	0.246	17.9%	29.9%	12.0%
All	Other fin.	1.146***	0.000	0.685***	0.000	41.2%	66.5%	25.3%
Germany	All	1.086***	0.000	0.051	0.626	31.0%	46.8%	15.9%
France	All	0.849***	0.000	0.208	0.185	29.3%	38.4%	9.1%
Italy	All	0.946***	0.000	0.377***	0.004	39.8%	47.5%	7.7%
Spain	All	0.829***	0.000	−0.265	0.282	11.1%	23.9%	12.7%

Note: The table shows the slope coefficients and p-values that result from the panel data regression of the cost of equity, using the ESG score as an information variable. Asterisks denote significance, where $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$. Each panel use a different number of lags for the ESG score, ranging from 0 to 2. Columns labeled 'R^2 plain' and 'R^2 full' show the R^2 statistics of the regressions ignoring or including the ESG score as an information variable, respectively. The column labeled 'Diff.' shows the difference between these statistics.

Table 2, their significance is lower, generally showing a positive relationship with $MV_{i,t} - BV_{i,t}$ for companies in financial sectors. Regarding ROE, Table B.2, B.5 and B.8 in Appendix B provide similar results to those shown in Table 3, with ESG variables providing a weak explanation for ROE across industries and countries, with the sole exception of the insurance sector, where the Environmental Score, Social Score and Governance Score provide R^2 statistics above 25% at a 2-year horizon. Notably, the effects of ESG policies on the cost of equity vary more across ESG indicators than for $MV_{i,t} - BV_{i,t}$ and $ROE_{i,t}$. Thus, while the Environmental Score and Governance Score in Tables B.3 and B.9 have lower explanatory power than the ESG score in Table 4, the Social Score in Table B.6 has high explanatory power in forecasting discount rates at a 2-year horizon, providing negative slope coefficients for most of the sectors and countries under study.

Hence, our results show that the smaller difference between market value and book value that results in the long-run for the best ESG performers is consistent with higher ESG scores forecasting higher long-term discount rates, rather than higher costs stemming from ESG policies. This suggests that investors are willing to accept lower returns in the short term – or equivalently, pay higher current prices in the stock markets – than in the long-run for those companies committed to ESG principles. Accordingly, good ESG performance generally translates into higher long-term discount rates and, consequently, lower market value at long horizons. Therefore, our results are consistent with ESG policies implying transitory effects on the cost of equity, which may be a consequence of time-varying investor preferences, long-term reputational penalties, or short-term market misvaluation.

Our findings are partially in line with those reported by Pástor et al. (2022), who show that U.S. stocks issued by firms committed to ESG principles (i.e. green stocks) outperformed stocks of firms with little commitment to ESG principles (brown stocks) for the period from 2012 to 2020. Moreover, based on the equilibrium model proposed by Pástor et al. (2021), the authors explain that such outperformance is directly related to shifts in customers' tastes for green products and investors' tastes for green holdings, which may partly explain the predictive power of ESG scores to forecast future stock returns. However, according to the authors, that does not mean that green stocks have higher expected returns than brown stocks. In fact, Pástor et al. (2022) explain that just the opposite is true, with green stocks exhibiting a lower unconditional cost of capital than brown stocks as a consequence of investors' green tastes and the fact that green assets are a better hedge against climate risk. Nonetheless, the authors also highlight the complexity of disentangling ex ante and ex post effects of ESG preferences by looking at realized returns in periods of changing ESG tastes. In this regard, our results are not contradictory with those provided by Pástor et al. (2022) given the conditional nature of the dynamic Ohlson model proposed in our paper and the unconditional form of the Pástor et al. (2021) model. In fact, as noted above, our results suggest that investors are conditionally willing to accept lower returns in the short term than in the long-run for green stocks, which does not mean that the unconditional cost of equity of green firms is higher. Moreover, following Cochrane (2011), our results are perfectly reconcilable with those obtained by Pástor et al. (2022) under specific term structures of time-varying expected returns. However, a thorough empirical analysis of the relationship between the dynamic Ohlson model and that of Pástor et al. (2021) requires considering potentially infinite horizons – or at least a sufficiently high number of periods –, which is a difficult task with the currently available ESG information.

Our results also complement the findings provided by Bofinger et al. (2022), who find that an improvement in a company's CSR leads to a higher ratio of actual to true firm value, mainly due to the current global trend of sustainable investing. Additionally, our results are consistent with the model proposed by Pedersen et al. (2021), in which the effects of ESG performance on equilibrium prices largely depend on the presence of different types of investors who are more or less aware of ESG policies.

4. Conclusions

Despite the general trend to include sustainability and CSR indicators to evaluate firm performance and non-financial value creation, the effect of such policies on the market value of companies is currently the subject of a lively debate. In this context, we propose a dynamic version of the Ohlson (1995) model that accounts for abnormal earnings using the economic profit under time-varying discount rates consistent with the Campbell and Shiller (1988) model, in order to differentiate between short term and long term implications of ESG performance on corporate value creation, as well as income and substitution effects.

Our results suggest that, although ESG policies imply almost no effects on value creation in the short-run, at longer horizons, better ESG performance results in a smaller difference between market value and book value, mainly due to substitution effects channeled to market value via higher long-term discount rates. These effects are particularly clear for firms in financial sectors, such as banks and other financial institutions, which are characterized by relatively low price-to-book value ratios and cost of capital. Hence, our results are consistent with ESG strategies implying transitory effects on the cost of equity and the market value of firms, which may result from non-separabilities in investor preferences that include ESG factors within marginal utility, among other reasons.

Based on these results, future research should address different aspects that may provide further explanation about the effects of ESG performance on corporate value. Regarding time horizon effects of ESG performance, our study faces the limitations that arise from a short time series on ESG information. Future research should not only expand the sample period studied, but also find different proxies for ESG variables for which longer time series are available. This could include well-established procedures in the asset pricing literature, such as mimicking portfolio analysis.

On the other hand, our results are sensitive to capital structure effects. Specifically, although our results suggest that ESG policies have small effects on ROE, return on equity is directly affected by the difference between return on invested capital minus the cost of borrowing, which may result in offsetting effects when analyzing the impact of ESG scores on ROE. Future research should study the extent to which other value creation measures, such as economic value added (EVA), may result in effects not considered in our research. Furthermore, further research on the effects of ESG performance on borrowing capacity is mandatory.

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Appendix A

See Table A.1.

Appendix B

See Tables B.1–B.9.

Table A.1
Indicators considered to determine Refinitiv® ESG Scores.

Environmental			Social				Governance		
Resource use	Emission	Environ. innov	Workforce	Human rights	Community	Product resp	Management	Shareholders	CSR strategy
Environment Management Team	Policy Emissions	Environ Products	Empl Satisfaction	Policy Freedom of Association	Policy Fair Competition	Customer Satisfaction	Board Functions	Shareholder Rights Policy	CSR Sust Cmte
Policy Water Efficiency	Targets Emissions	Noise Reduction	Diversity and Opp	Policy Child Labor	Policy Bribery and Corruption	Policy Customer Health & Safety	Board Meeting Att	Voting Cap Percentage	Integrated Strategy in MD&A
Policy Energy Efficiency	Biodiversity Impact Reduction	Fleet Fuel Consumption	Women Employees	Policy Forced Labor	Policy Business Ethics	Policy Data Privacy	Succession Plan	Director Election Majority Req	Global Compact Signatory
Policy Sustainable Packaging	Flaring Gases	Hybrid Vehicles	Women Managers	Policy Human Rights	Improvement Tools Busi Ethics	Policy Responsible Marketing	External Consult	Shareholders Vote on Executive Pay	Stakeholder Engagement
Policy Environ Supply Chain	Cement CO2 Equivalents Emis	Fleet CO2 Emissions	HRC Corporate Equality Index	Fund Human Rights ILO UN	Whistleblower Protection	Policy Fair Trade	Adt Cmte Mgt Ind	Public Availability	CSR Sust Reporting
Targets Water Efficiency	Ozone-Depleting Substances	Environ Assets Under Mgt	Flexible Hours	Human Rights Contractor	Policy Community Involvement	Product Resp Monitoring	Comp Cmte Ind/Mgt	Corporate Statutes	GRI Report Guidelines
Targets Energy Efficiency	NOx and SOx Emissions Rd	Nuclear Production	Day Care Services	Ethical Trading Initiative ETI	OECD Guidelines for Multinational Enterprises	Product Access Low Price	Nom Cmte Ind	Veto Power or Golden share	CSR Sust Report
Environ Materials Sourcing	e-Waste Reduction	Labeled Wood Percentage	Empl With Disabi	Human Rights Breaches Contr	Extractive Industries Transparency Initiative	Healthy Food or Products	Nom Cmte Involv	State Owned Enterprise SOE	Global Activities
Toxic Chemicals Reduction	Emissions Trading	Organic Products Initiatives	Trade Union Repr		Community Lending and Investments	Embryonic Stem Cell Research	Board Attendance	Equal Shareholder Rights	CSR Sust External Audit
Cement Energy Use	Environ Ptr	GMO Products	Turnover of Empl		Product Sales at Discount to Emerging Markets	Retailing Responsibility	Board Structure	Anti Takeover Devices Above Two	
Green Buildings	EMS Certified	Agrochemical Products	Strikes		Diseases of the Developing World	QMS Certified Percent	Brd Bkgd and Skills	Auditor Tenure	
Water Recycled	Environ Restoration Init	Animal Testing	Salary Gap		Critical Country 1	Quality Mgt Systems	Board Gender Div	Litigation Expenses	
Environ Supply Chain Mgmt	Staff Trans Impact Reduction	Renewable/Clean Energy Products	Net Empl Creation		Corporate Resp Awards		Brd Specific Skills	Non-audit to Audit Fees Ratio	
Env Supply Chain Ptr Termination	Climate Change Comm Risks	Water Tech	Announced Layoffs To Total Employees		Total Donations To Revenues		Board Tenure		
Land Environ Impact Reduction	Self-Reported Environ Fines	Sustainable Building Products	Health & Safety				Non-Exec Brd Mbr		
Environ Supply Chain Monitoring	Estimated CO2 Equivalents Emis	Real Estate Sust Certifications	Employees Health & Safety Team				Ind Board Members		
Total Energy Use To Revenues	VOC or Particulate Matter Emis Red	Env R&D Expnd To Revenues	Empl Health Safety				CEO-Chairman Sep		
Renewable Energy Use Ratio	Total Waste To Revenues USD	Equator Principles or Env Project Fin	Training Hours				Brd Member Affl		
Water Use To Revenues	Waste Recycled To Total Waste	Renewable Energy Supply	Employees Health & Safety OHSAS				Brd Indiv Re-election		
	Total Hazardous Waste To Rev	Product Impact Minimization	Supply Chain Health & Safety				Board Cultural Diversity, Percent		
	Water Pollutant Emis To Revenues		Occ Diseases				Executive Members Gender Diversity		
	Environ Expnd Inv		HIV-AIDS Program				Executive Comp		
			Injuries To MM Hrs				Comp Impr Tools		
			Lost To Total Days				CEO Compensation		
			Trng and Dev Plcy				Total Senior Exec		
			Avg Training Hrs				Sh Approval Stock Comp Plan		
			Internal Promotion				Exec Indiv Comp		
			Supplier ESG training				Highest Rem Pkg		
			Training Costs/Empl				Exec Comp LT Obj		
							Sust Comp Incentives		
							Int Audit Dept Report		

Table B.1
Regression results for $MV_{i,t} - BV_{i,t}$ using the Environmental Score as information variable.

Country	Sector	Φ_{EP}	$\sigma(\Phi_{EP})$	$\Phi_E \cdot 10^{-3}$	$\sigma(\Phi_E) \cdot 10^{-3}$	R^2 plain	R^2 full	Diff.
Panel A: Number of lags = 0								
All	All	−1.133***	0.120	−0.002	0.002	16.5%	17.3%	0.9%
All	Banks	−1.295***	0.067	0.005	0.005	83.2%	84.3%	1.0%
All	Industrial	−1.223***	0.313	−0.003	0.002	14.4%	17.0%	2.6%
All	Insurance	0.740***	0.074	−0.086***	0.009	70.7%	80.6%	9.9%
All	Other fin.	−1.948***	0.306	0.000	0.000	51.4%	53.3%	1.9%
Germany	All	−0.905***	0.183	−0.005	0.006	24.4%	25.2%	0.8%
France	All	−1.465***	0.260	−0.012	0.008	15.9%	17.8%	1.9%
Italy	All	−1.685***	0.181	−0.001	0.001	43.8%	44.0%	0.2%
Spain	All	3.749***	0.871	−0.003	0.004	22.9%	24.5%	1.6%
Panel B: Number of lags = 1								
All	All	−1.231***	0.146	−0.002	0.002	16.5%	19.7%	3.2%
All	Banks	−1.303***	0.083	0.001	0.004	83.2%	90.2%	7.0%
All	Industrial	−1.201***	0.316	−0.002	0.002	14.4%	18.0%	3.6%
All	Insurance	−2.034***	0.310	0.032	0.035	70.7%	81.2%	10.5%
All	Other fin.	−1.891***	0.371	0.002	0.003	51.4%	57.5%	6.1%
Germany	All	−1.000***	0.231	−0.004	0.006	24.4%	27.6%	3.1%
France	All	−1.592***	0.302	−0.012	0.010	15.9%	20.0%	4.1%
Italy	All	−1.472***	0.231	−0.001	0.001	43.8%	34.3%	−9.5%
Spain	All	3.786***	0.901	−0.012	0.016	22.9%	28.2%	5.3%
Panel C: Number of lags = 2								
All	All	−1.277***	0.159	−0.004	0.005	16.5%	23.2%	6.7%
All	Banks	−1.310***	0.084	0.015	0.010	83.2%	96.9%	13.7%
All	Industrial	−0.994*	0.392	−0.002	0.003	14.4%	18.1%	3.7%
All	Insurance	−1.884***	0.297	0.002*	0.001	70.7%	88.7%	18.0%
All	Other fin.	−2.009***	0.391	0.002	0.003	51.4%	78.5%	27.2%
Germany	All	−1.055***	0.255	−0.000	0.000	24.4%	30.8%	6.4%
France	All	−1.655***	0.316	−0.015	0.010	15.9%	25.3%	9.4%
Italy	All	−1.515***	0.264	−0.001	0.001	43.8%	40.4%	−3.4%
Spain	All	−0.956**	0.302	−0.014	0.016	22.9%	23.8%	0.9%

Note: The table shows the slope coefficients and standard errors that result from the panel data regression of the difference between the market value and the book value, using the Environmental Score as an information variable. Asterisks denote significance, where $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$. Each panel use a different number of lags for the Environmental Score, ranging from 0 to 2. Columns labeled 'R^2 plain' and 'R^2 full' show the R^2 statistics of the regressions ignoring or including the ESG score as an information variable, respectively. The column labeled 'Diff.' shows the difference between these statistics.

Table B.2
Regression results for $ROE_{i,t}$ using the Environmental Score as information variable.

Country	Sector	b_E^{ROE}	$p\left(b_E^{ROE}\right)$	R^2
Panel A: Number of lags = 0				
All	All	0.001	0.858	0.0%
All	Banks	0.014	0.532	0.4%
All	Industrial	0.004	0.746	0.0%
All	Insurance	−0.007	0.145	5.9%
All	Other fin.	0.000	0.909	0.3%
Germany	All	−0.001	0.886	0.0%
France	All	0.068	0.402	0.1%
Italy	All	0.009	0.333	0.6%
Spain	All	−0.060	0.837	0.0%
Panel B: Number of lags = 1				
All	All	−0.001	0.947	0.0%
All	Banks	0.007	0.751	0.1%
All	Industrial	−0.005	0.877	0.0%
All	Insurance	0.005	0.113	18.6%
All	Other fin.	0.000	0.957	0.6%
Germany	All	0.000	0.939	0.3%
France	All	−0.154*	0.094	1.0%
Italy	All	0.017	0.304	0.4%
Spain	All	−0.301	0.649	0.2%

(continued on next page)

Table B.2 (*continued*).

Country	Sector	b_E^{ROE}	$p\left(b_E^{ROE}\right)$	R^2
Panel C: Number of lags = 2				
All	All	0.000	0.994	0.0%
All	Banks	0.037	0.544	0.0%
All	Industrial	0.026	0.818	0.0%
All	Insurance	0.001	0.884	27.8%
All	Other fin.	0.000	0.864	2.1%
Germany	All	0.001	0.832	0.0%
France	All	0.067	0.688	0.1%
Italy	All	−0.004	0.861	7.3%
Spain	All	0.175	0.891	0.0%

Note: The table shows the slope coefficient and the p-value that result from the panel data regression of ROE, using the Environmental Score as an information variable. Asterisks denote significance, where $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$. The table also provides the R^2 statistic of the regressions. Each panel use a different number of lags for the Environmental Score, ranging from 0 to 2.

Table B.3
Regression results for $R_{i,t}$ using the Environmental Score as information variable.

Country	Sector	b_{RM}^R	$p\left(b_{RM}^R\right)$	b_E^R	$p\left(b_E^R\right)$	R^2 plain	R^2 full	Diff.
Panel A: Number of lags = 0								
All	All	0.991***	0.000	−0.001	0.834	27.8%	27.2%	−0.5%
All	Banks	0.966***	0.000	−0.029	0.657	37.5%	38.0%	0.4%
All	Industrial	1.014***	0.000	−0.005	0.537	27.5%	26.9%	−0.6%
All	Insurance	0.416***	0.003	−0.045	0.127	17.9%	20.1%	2.2%
All	Other fin.	1.038***	0.000	0.002	0.657	41.2%	45.4%	4.2%
Germany	All	1.226***	0.000	0.002	0.773	31.0%	30.0%	−1.0%
France	All	0.891***	0.000	0.005	0.940	29.3%	28.5%	−0.8%
Italy	All	1.006***	0.000	−0.018*	0.063	39.8%	41.4%	1.6%
Spain	All	0.599***	0.000	0.076	0.460	11.1%	11.6%	0.5%
Panel B: Number of lags = 1								
All	All	0.923***	0.000	0.005	0.404	27.8%	26.5%	−1.3%
All	Banks	0.972***	0.000	0.114	0.220	37.5%	49.1%	11.6%
All	Industrial	0.946***	0.000	0.019	0.375	27.5%	25.8%	−1.6%
All	Insurance	0.358**	0.017	0.023	0.445	17.9%	19.2%	1.3%
All	Other fin.	0.852***	0.000	0.003	0.506	41.2%	39.0%	−2.2%
Germany	All	1.150***	0.000	0.002	0.795	31.0%	29.2%	−1.8%
France	All	0.831***	0.000	−0.047	0.587	29.3%	27.4%	−1.9%
Italy	All	0.893***	0.000	0.049*	0.085	39.8%	38.7%	−1.1%
Spain	All	0.633***	0.000	−0.030	0.869	11.1%	14.4%	3.3%
Panel C: Number of lags = 2								
All	All	0.940***	0.000	0.001	0.867	27.8%	35.3%	7.5%
All	Banks	0.861***	0.000	0.089	0.650	37.5%	54.5%	17.0%
All	Industrial	0.968***	0.000	−0.019	0.684	27.5%	35.7%	8.2%
All	Insurance	0.386**	0.035	−0.005	0.892	17.9%	23.3%	5.4%
All	Other fin.	1.182***	0.000	0.000	0.949	41.2%	51.3%	10.1%
Germany	All	1.089***	0.000	0.001	0.887	31.0%	46.9%	15.9%
France	All	0.870***	0.000	0.199*	0.098	29.3%	38.3%	9.1%
Italy	All	0.906***	0.000	0.045	0.249	39.8%	39.9%	0.1%
Spain	All	0.792***	0.000	0.148	0.604	11.1%	22.9%	11.8%

Note: The table shows the slope coefficients and p-values that result from the panel data regression of the cost of equity, using the Environmental Score as an information variable. Asterisks denote significance, where $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$. Each panel use a different number of lags for the Environmental Score, ranging from 0 to 2. Columns labeled 'R^2 plain' and 'R^2 full' show the R^2 statistics of the regressions ignoring or including the ESG score as an information variable, respectively. The column labeled 'Diff.' shows the difference between these statistics.

Table B.4
Regression results for $MV_{i,t} - BV_{i,t}$ using the Social Score as information variable.

Country	Sector	Φ_{EP}	$\sigma(\Phi_{EP})$	$\Phi_S \cdot 10^{-3}$	$\sigma(\Phi_S) \cdot 10^{-3}$	R^2 plain	R^2 full	Diff.
Panel A: Number of lags = 0								
All	All	−1.144***	0.116	−0.002*	0.001	16.5%	17.4%	0.9%
All	Banks	−1.302***	0.067	0.018	0.013	83.2%	84.7%	1.5%
All	Industrial	−1.229***	0.310	−0.006	0.005	14.4%	16.7%	2.3%
All	Insurance	−2.073***	0.287	−0.128***	0.035	70.7%	78.0%	7.2%
All	Other fin.	−1.974***	0.272	0.003	0.006	51.4%	53.1%	1.8%
Germany	All	−0.943***	0.173	−0.008	0.005	24.4%	25.8%	1.3%
France	All	−1.450***	0.255	−0.004	0.006	15.9%	17.3%	1.3%
Italy	All	−1.669***	0.177	0.001	0.003	43.8%	43.9%	0.1%
Spain	All	3.689***	0.856	−0.005	0.006	22.9%	24.1%	1.2%
Panel B: Number of lags = 1								
All	All	−1.252***	0.144	−0.004	0.003	16.5%	19.9%	3.5%
All	Banks	−1.292***	0.081	0.021	0.013	83.2%	90.8%	7.6%
All	Industrial	−1.197***	0.312	−0.006	0.005	14.4%	18.1%	3.7%
All	Insurance	−2.056***	0.298	0.011	0.014	70.7%	79.9%	9.1%
All	Other fin.	1.823***	0.322	0.005	0.009	51.4%	57.5%	6.1%
Germany	All	−1.030***	0.223	−0.007	0.005	24.4%	28.7%	4.3%
France	All	−1.609***	0.301	−0.011	0.012	15.9%	19.7%	3.8%
Italy	All	−1.474***	0.226	−0.001	0.002	43.8%	34.1%	−9.7%
Spain	All	3.813***	0.896	−0.006	0.006	22.9%	28.3%	5.4%
Panel C: Number of lags = 2								
All	All	−1.310***	0.157	−0.005	0.004	16.5%	23.6%	7.1%
All	Banks	−1.336***	0.090	−0.006	0.006	83.2%	96.7%	13.5%
All	Industrial	−0.986*	0.390	−0.004	0.004	14.4%	18.3%	3.9%
All	Insurance	−1.979***	0.331	0.008	0.010	70.7%	88.2%	17.5%
All	Other fin.	−2.055***	0.384	0.006	0.005	51.4%	79.3%	28.0%
Germany	All	−1.144***	0.249	−0.006	0.005	24.4%	32.3%	7.8%
France	All	−1.638***	0.321	−0.014	0.022	15.9%	24.1%	8.2%
Italy	All	−1.494***	0.259	−0.003	0.004	43.8%	40.0%	−3.8%
Spain	All	−0.933**	0.304	−0.007	0.013	22.9%	23.8%	0.9%

Note: The table shows the slope coefficients and standard errors that result from the panel data regression of the difference between the market value and the book value, using the Social Score as an information variable. Asterisks denote significance, where $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$. Each panel use a different number of lags for the Social Score, ranging from 0 to 2. Columns labeled 'R^2 plain' and 'R^2 full' show the R^2 statistics of the regressions ignoring or including the ESG score as an information variable, respectively. The column labeled 'Diff.' shows the difference between these statistics.

Table B.5
Regression results for $ROE_{i,t}$ using the Social Score as information variable.

Country	Sector	b_S^{ROE}	$p\left(b_S^{ROE}\right)$	R^2
Panel A: Number of lags = 0				
All	All	0.010	0.579	0.0%
All	Banks	0.044	0.213	1.7%
All	Industrial	0.011	0.600	0.0%
All	Insurance	−0.002	0.564	2.7%
All	Other fin.	−0.009	0.558	1.1%
Germany	All	0.047	0.181	0.4%
France	All	0.049	0.470	0.0%
Italy	All	0.053	0.326	0.5%
Spain	All	−0.003	0.938	0.0%

(*continued on next page*)

Table B.5 (*continued*).

Country	Sector	b_S^{ROE}	$p\left(b_S^{ROE}\right)$	R^2
Panel B: Number of lags = 1				
All	All	0.004	0.860	0.0%
All	Banks	0.012	0.713	0.0%
All	Industrial	0.004	0.874	0.0%
All	Insurance	0.000	0.955	5.6%
All	Other fin.	0.018	0.494	2.6%
Germany	All	0.005	0.887	0.2%
France	All	−0.137	0.146	0.8%
Italy	All	0.042	0.386	0.2%
Spain	All	0.000	0.992	0.0%
Panel C: Number of lags = 2				
All	All	0.199	0.131	0.5%
All	Banks	0.128*	0.069	7.4%
All	Industrial	0.236	0.153	0.5%
All	Insurance	−0.006	0.732	28.6%
All	Other fin.	0.043	0.505	4.5%
Germany	All	−0.033	0.707	0.1%
France	All	−0.048	0.778	0.1%
Italy	All	0.114*	0.056	8.7%
Spain	All	1.674*	0.055	5.1%

Note: The table shows the slope coefficient and the p-value that result from the panel data regression of ROE, using the Social Score as an information variable. Asterisks denote significance, where $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$. The table also provides the R^2 statistic of the regressions. Each panel use a different number of lags for the Social Score, ranging from 0 to 2.

Table B.6
Regression results for $R_{i,t}$ using the Social Score as information variable.

Country	Sector	b_{RM}^R	$p\left(b_{RM}^R\right)$	b_S^R	$p\left(b_S^R\right)$	R^2 plain	R^2 full	Diff.
Panel A: Number of lags = 0								
All	All	1.001***	0.000	0.010	0.414	27.8%	27.8%	0.0%
All	Banks	0.972***	0.000	0.047	0.660	37.5%	37.4%	−0.1%
All	Industrial	1.031***	0.000	0.012	0.375	27.5%	27.5%	0.1%
All	Insurance	0.418***	0.003	−0.043	0.109	17.9%	22.0%	4.1%
All	Other fin.	0.972***	0.000	−0.025	0.653	41.2%	41.4%	0.2%
Germany	All	1.239***	0.000	0.031	0.476	31.0%	31.1%	0.1%
France	All	0.916***	0.000	−0.045	0.444	29.3%	29.4%	0.1%
Italy	All	0.985***	0.000	−0.087	0.191	39.8%	40.3%	0.5%
Spain	All	0.583***	0.000	0.011	0.402	11.1%	11.5%	0.3%
Panel B: Number of lags = 1								
All	All	0.933***	0.000	−0.009	0.523	27.8%	27.0%	−0.8%
All	Banks	0.980***	0.000	0.007	0.949	37.5%	47.7%	10.2%
All	Industrial	0.963***	0.000	−0.010	0.496	27.5%	26.4%	−1.1%
All	Insurance	0.377***	0.007	0.020	0.433	17.9%	20.9%	3.0%
All	Other fin.	0.831***	0.000	0.009	0.924	41.2%	36.4%	−4.8%
Germany	All	1.146***	0.000	0.026	0.632	31.0%	29.7%	−1.3%
France	All	0.844***	0.000	−0.075	0.389	29.3%	28.0%	−1.3%
Italy	All	0.891***	0.000	−0.007	0.921	39.8%	37.9%	−1.9%
Spain	All	0.628***	0.000	−0.011	0.432	11.1%	14.6%	3.5%
Panel C: Number of lags = 2								
All	All	0.940***	0.000	−0.018	0.765	27.8%	35.5%	7.7%
All	Banks	0.962***	0.000	0.733***	0.001	37.5%	60.9%	23.4%
All	Industrial	0.965***	0.000	−0.122*	0.075	27.5%	36.6%	9.1%
All	Insurance	0.420**	0.010	−0.123	0.288	17.9%	29.1%	11.3%
All	Other fin.	1.063***	0.000	0.533***	0.000	41.2%	63.3%	22.1%
Germany	All	1.052***	0.000	−0.118	0.171	31.0%	47.4%	16.5%
France	All	0.862***	0.000	−0.014	0.908	29.3%	37.7%	8.4%
Italy	All	0.965***	0.000	0.385***	0.001	39.8%	50.2%	10.4%
Spain	All	0.819***	0.000	−0.111	0.589	11.1%	22.9%	11.8%

Note: The table shows the slope coefficients and p-values that result from the panel data regression of the cost of equity, using the Social Score as an information variable. Asterisks denote significance, where $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$. Each panel use a different number of lags for the Social Score, ranging from 0 to 2. Columns labeled 'R^2 plain' and 'R^2 full' show the R^2 statistics of the regressions ignoring or including the ESG score as an information variable, respectively. The column labeled 'Diff.' shows the difference between these statistics.

Table B.7
Regression results for $MV_{i,t} - BV_{i,t}$ using the Governance Score as information variable.

Country	Sector	Φ_{EP}	$\sigma(\Phi_{EP})$	$\Phi_G \cdot 10^{-3}$	$\sigma(\Phi_G) \cdot 10^{-3}$	R^2 plain	R^2 full	Diff.
Panel A: Number of lags = 0								
All	All	−1.139***	0.117	−0.005	0.003	16.5%	17.5%	1.0%
All	Banks	−1.295***	0.064	0.011	0.008	83.2%	84.6%	1.4%
All	Industrial	−1.231***	0.310	−0.006*	0.003	14.4%	17.0%	2.6%
All	Insurance	−2.029***	0.250	0.016*	0.007	70.7%	74.9%	4.2%
All	Other fin.	−1.979***	0.272	−0.004	0.005	51.4%	53.9%	2.6%
Germany	All	−0.940***	0.174	−0.010*	0.004	24.4%	26.4%	1.9%
France	All	−1.441***	0.255	−0.007	0.005	15.9%	17.7%	1.7%
Italy	All	−1.685***	0.172	0.004*	0.002	43.8%	44.8%	1.0%
Spain	All	3.804***	0.853	−0.003	0.003	22.9%	24.8%	2.0%
Panel B: Number of lags = 1								
All	All	−1.245***	0.144	−0.005	0.003	16.5%	20.0%	3.5%
All	Banks	−1.304***	0.080	0.006	0.006	83.2%	90.6%	7.4%
All	Industrial	−1.217***	0.312	−0.006*	0.003	14.4%	18.2%	3.8%
All	Insurance	−2.022***	0.297	0.027	0.015	70.7%	82.3%	11.6%
All	Other fin.	1.817***	0.315	−0.007	0.008	51.4%	58.1%	6.7%
Germany	All	−1.042***	0.223	−0.005	0.004	24.4%	28.5%	4.1%
France	All	−1.575***	0.304	−0.008	0.006	15.9%	19.9%	3.9%
Italy	All	−1.482***	0.223	−0.004	0.003	43.8%	34.7%	−9.1%
Spain	All	3.877***	0.923	−0.002	0.003	22.9%	28.1%	5.2%
Panel C: Number of lags = 2								
All	All	−1.315***	0.155	−0.006*	0.003	16.5%	24.0%	7.5%
All	Banks	−1.305***	0.086	−0.002	0.003	83.2%	96.5%	13.3%
All	Industrial	−1.007*	0.389	−0.006*	0.003	14.4%	18.8%	4.4%
All	Insurance	−1.959***	0.304	0.004	0.004	70.7%	89.0%	18.3%
All	Other fin.	−2.084***	0.328	−0.010*	0.004	51.4%	82.2%	30.8%
Germany	All	−1.125***	0.244	−0.007	0.004	24.4%	33.2%	8.8%
France	All	−1.660***	0.315	−0.010	0.006	15.9%	25.0%	9.0%
Italy	All	−1.461***	0.259	−0.008	0.012	43.8%	40.5%	−3.3%
Spain	All	−0.960**	0.309	−0.002	0.005	22.9%	23.5%	0.6%

Note: The table shows the slope coefficients and standard errors that result from the panel data regression of the difference between the market value and the book value, using the Governance Score as an information variable. Asterisks denote significance, where $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$. Each panel use a different number of lags for the Governance Score, ranging from 0 to 2. Columns labeled 'R^2 plain' and 'R^2 full' show the R^2 statistics of the regressions ignoring or including the ESG score as an information variable, respectively. The column labeled 'Diff.' shows the difference between these statistics.

Table B.8
Regression results for $ROE_{i,t}$ using the Governance Score as information variable.

Country	Sector	b_G^{ROE}	$p\left(b_G^{ROE}\right)$	R^2
Panel A: Number of lags = 0				
All	All	0.027	0.279	0.1%
All	Banks	0.074**	0.032	5.3%
All	Industrial	0.030	0.308	0.1%
All	Insurance	0.005	0.515	2.6%
All	Other fin.	0.006	0.744	0.8%
Germany	All	0.032	0.144	0.4%
France	All	0.057	0.116	0.4%
Italy	All	0.062	0.108	1.1%
Spain	All	−0.050	0.756	0.1%

(*continued on next page*)

Table B.8 (*continued*).

Country	Sector	b_G^{ROE}	$p\left(b_G^{ROE}\right)$	R^2
Panel B: Number of lags = 1				
All	All	0.001	0.974	0.0%
All	Banks	−0.028	0.321	0.8%
All	Industrial	0.003	0.942	0.0%
All	Insurance	0.013**	0.049	15.2%
All	Other fin.	−0.008	0.782	1.9%
Germany	All	0.007	0.762	0.2%
France	All	−0.026	0.528	0.2%
Italy	All	−0.006	0.866	0.0%
Spain	All	0.057	0.823	0.0%
Panel C: Number of lags = 2				
All	All	−0.040	0.448	0.1%
All	Banks	0.026	0.633	0.4%
All	Industrial	−0.043	0.479	0.1%
All	Insurance	−0.003	0.693	25.6%
All	Other fin.	−0.116*	0.092	12.4%
Germany	All	0.001	0.979	0.0%
France	All	−0.076	0.280	0.7%
Italy	All	−0.026	0.638	7.7%
Spain	All	−0.243	0.532	0.6%

Note: The table shows the slope coefficient and the p-value that result from the panel data regression of ROE, using the Governance Score as an information variable. Asterisks denote significance, where $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$. The table also provides the R^2 statistic of the regressions. Each panel use a different number of lags for the Governance Score, ranging from 0 to 2.

Table B.9
Regression results for $R_{i,t}$ using the Governance score as information variable.

Country	Sector	b_{RM}^R	$p\left(b_{RM}^R\right)$	b_G^R	$p\left(b_G^R\right)$	R^2 plain	R^2 full	Diff.
Panel A: Number of lags = 0								
All	All	0.993***	0.000	0.075***	0.000	27.8%	28.6%	0.9%
All	Banks	0.970***	0.000	−0.062	0.564	37.5%	37.9%	0.3%
All	Industrial	1.023***	0.000	0.087***	0.000	27.5%	28.6%	1.1%
All	Insurance	0.460***	0.001	−0.007	0.900	17.9%	17.9%	0.0%
All	Other fin.	0.983***	0.000	−0.019	0.743	41.2%	41.3%	0.1%
Germany	All	1.216***	0.000	0.107***	0.000	31.0%	32.9%	2.0%
France	All	0.913***	0.000	0.051	0.130	29.3%	29.6%	0.4%
Italy	All	0.989***	0.000	−0.019	0.701	39.8%	39.9%	0.1%
Spain	All	0.577***	0.000	0.030	0.575	11.1%	11.3%	0.2%
Panel B: Number of lags = 1								
All	All	0.933***	0.000	0.002	0.935	27.8%	27.0%	−0.8%
All	Banks	0.981***	0.000	−0.056	0.624	37.5%	47.8%	10.3%
All	Industrial	0.962***	0.000	0.002	0.949	27.5%	26.3%	−1.1%
All	Insurance	0.361**	0.011	−0.050	0.351	17.9%	21.5%	3.6%
All	Other fin.	0.816***	0.000	−0.028	0.753	41.2%	36.5%	−4.7%
Germany	All	1.154***	0.000	0.006	0.865	31.0%	29.6%	−1.4%
France	All	0.848***	0.000	0.016	0.673	29.3%	27.8%	−1.4%
Italy	All	0.887***	0.000	−0.029	0.658	39.8%	38.0%	−1.8%
Spain	All	0.620***	0.000	−0.021	0.763	11.1%	14.2%	3.1%
Panel C: Number of lags = 2								
All	All	0.937***	0.000	0.012	0.607	27.8%	35.5%	7.8%
All	Banks	0.852***	0.000	0.331**	0.039	37.5%	62.7%	25.2%
All	Industrial	0.970***	0.000	0.014	0.585	27.5%	36.1%	8.6%
All	Insurance	0.478***	0.004	−0.077	0.181	17.9%	31.5%	13.6%
All	Other fin.	1.014***	0.000	−0.074	0.687	41.2%	41.4%	0.2%
Germany	All	1.072***	0.000	0.032	0.307	31.0%	47.6%	16.6%
France	All	0.841***	0.000	0.051	0.319	29.3%	38.1%	8.8%
Italy	All	0.901***	0.000	0.091	0.414	39.8%	39.7%	−0.1%
Spain	All	0.828***	0.000	−0.142	0.100	11.1%	25.5%	14.4%

Note: The table shows the slope coefficients and p-values that result from the panel data regression of the cost of equity, using the Governance Score as an information variable. Asterisks denote significance, where $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$. Each panel use a different number of lags for the Governance Score, ranging from 0 to 2. Columns labeled 'R^2 plain' and 'R^2 full' show the R^2 statistics of the regressions ignoring or including the ESG score as an information variable, respectively. The column labeled 'Diff.' shows the difference between these statistics.

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