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GRA 19703 Master Thesis

IPO Underpricing and ESG firms: An empirical study

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Abstract

Firm decision-making in the context of Initial Public Offerings is centered around the problem of information asymmetry, and the resulting differences in valuations between new issue participants. We aim to study the ‘unexplained’ component of IPO underpricing equations that underlie such a notion, where ESG disclosures can reduce uncertainty in terms of market expectations. We classify firms based on the level of ESG inherent in the organization, and test whether these levels are weighed in the offer price decision and subsequent first-day returns. Controlling for firm-level factors, we find that although general ESG efforts marginally improve underpricing predictions, there exists no significant variation between these values for different classes of ESG firms.

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1. Introduction and motivation

In recent years, efforts for sustainability in business and investment practices have become increasingly relevant for all participants of global financial markets. With the advent of several black swan events including political turmoil, wildfires, and pandemics, and the subsequent increase in systemic risk in these markets (Rizwan et al., 2020), there is greater pressure on firms to adopt risk management in Environmental, Social, and Governance (ESG) activities. Firms face greater direct costs related to regulation and lack of efficiency in resource utilization when these risks are not managed well. These material factors also have a proven impact on financial performance and firm viability in a market with ESG-aware investors who seek sustainable investments, hampering firms' access to capital and increasing sourcing costs (Krüger, 2015). This trend in investors expanding their decision-making criteria to include the social impact of their investments, can be attributed to a plethora of literature suggesting the importance of ESG risk-based asset pricing (Friede et al., 2015) and to the intrinsic value they derive from such investments as they prioritize the preservation and sharing of wealth in the long term.

In association with restricted access to capital, firms raising new funds through Initial Public Offerings (IPOs) have also been subjected to greater scrutiny on their ESG practices. An important part of the IPO process is the pricing of the firm's shares, which hinges on an accurate understanding of the investors' willingness to pay based on the amount of information available to them, adjusted for their subjective investment criteria. IPO underpricing is a measure of "money left on the table" due to the IPO offer price being lower than market expectation. This adds relevance to the type of information shared by the company and the method of communicating it, to reduce informational frictions. We believe that ESG disclosure reduces information asymmetry related to the firm's risk management and sustainability efforts, thereby leading to an increased demand for such communication, while promoting transparency and trust for ESG-geared investors.

To discuss this statement at a firm-level, we build on similar research suggested at a country-level by Baker et al. (2021) along with other underpricing and ESG models detailed in previous literature. We identify the following research question for our empirical study:

“To what extent does IPO underpricing differ between classes of ESG firms?”

Here, we are interested to examine the differences in the degree of IPO underpricing between classes of ESG firms, with firm-level control factors, to understand whether investors perceive and reflect any difference in these firms’ ESG practices. Classes helps us differentiate companies with strong ESG "purpose" and others without ESG as a core value but with mild or low ESG efforts. Using regional samples to run this analysis, we can further conclude on variation in this spread across the regions considered.

At this point, we clarify an important understanding that sets the tone of this paper. In IPO studies, researchers primarily focus on *underpricing* or *first-day returns*. The term *underpricing* is commonly used in both the industry as well as research papers as an expression for first-day returns in the aftermath of an IPO. Thus, first-day returns and underpricing may be used interchangeably under most contexts. However, we make a distinction such that the term *underpricing* is closely linked to a firm’s pricing decision, where a notable difference between offer price and closing price on the first day of listing is driven by a firm’s undervaluation of its share, essentially a firm’s deliberate or mistakenly false understanding of market expectation. Conversely, the interpretation for *first-day returns* can be expected to lean towards the closing price of an IPO, with the hypothesis that the difference between offer/closing price is driven by higher demand for the share (Agarwal et al., 2008). Although this is an excellent definition to capture market sentiment in IPOs (especially for demand driven by ESG), our primary goal is to understand this phenomenon from the firm’s perspective, i.e. as underpricing.

We look at firms that have participated in an initial public offering across a fixed time period of seven years – spanning 2014 to 2020. This cross-sectional data is collected across 2 broad regions namely the United States of America and the *Nordics* region, called so for the countries included in the set i.e. Norway, Denmark, and Sweden. We are interested in these two regions primarily for their stark differences in yearly IPO activity, country-level ESG regulations and their effects, and the subjective importance placed on sustainability by each firm within these samples.

To translate our thinking into a testable hypothesis, we consider the offer price decision taken by firms during its IPO. This decision is influenced by a variety of firm-level factors such as company and offer size, choice of underwriter, and existing capital structure. Building on our curiosity to understand this variable across regions, we add dummies to model the country effects on such decisions, along with year and industry. Controlling for these measures, we build regression models to understand the impact of a firm's ESG class on its underpricing. We hypothesize that if a firm undertakes ESG efforts, the level of effort is negatively related to the level of underpricing where a firm with high ESG values experiences lower underpricing than firms with a moderate or low ESG integration.

Using a weighed score for each pillar of ESG i.e. Environment, Social, Governance efforts, we classify firms into four classes based on their ESG integration levels that range from high to low (C1 to C4). In our original dataset of IPOs, excluding firms that do not disclose ESG information, or those for whom such data is unavailable, can cause significant selection bias. We test for this using appropriate selection models discussed further in the text. For our sample, we find that this bias is negligible, and modelling for it does not improve robustness of our results. In order to avoid truncating the data, we include all firms in our sample (with or without an ESG class), and introduce a nested variable approach for firms that have an ESG score and are further segregated into ESG classes.

Our analysis shows the introduction of ESG efforts in an underpricing equation marginally improve its ability to predict and explain pricing in the context of IPOs. When we model the classes of ESG firms into the regression, we find that there is no significant contribution of the firm ESG class on underpricing. This indicates that IPO underpricing does not differ between classes on ESG firms in our dataset.

The implications of such results can be construed as inefficient pricing of ESG risks and efforts in the market for IPOs, where the known difference in ESG classes and the resulting benefits are not captured fully by the investors in their valuations. This entails a possibility of edging the market for short-term gain while the market assimilates this information. As for the firms that issue shares in an IPOs, this result can signal that their efforts are not communicated to the general investor accurately, hampering their chances of achieving a fair valuation that is indicative of their level of ESG alignment and investments in global financial markets.

Further development on our preliminary research is done through out-of-sample predictions for IPOs that took place in 2021, and a brief analysis of the post-IPO performance of different classes of ESG firms.

2. Literature review

In order to place our proposed research question within available works in the topic of IPO underpricing and ESG firms, we look at a few articles that map the relevance of ESG on firm performance as a whole, on funding, and finally on underpricing.

2.1. IPO underpricing

An Initial Public Offering is a widely employed method of raising capital for firms, stemming from the advantages of liquidity and diversity offered by the financial markets, allowing the firms to set their terms more freely. However, IPOs bear higher costs compared to other modes such as Seasoned Public Offerings or debt, along with the persistent indirect cost of underpricing (Lee et al., 1996). Despite extensive research, studies fail to agree on a common model for determining underpricing, and argue for several reasons that causes this phenomenon. Engelen and van Essen (2010) provide a robust underpricing model that draws from several published papers, which can be modified to build a more detailed analysis to address specific research questions. Firm-specific factors that partly explain underpricing include firm age (older the firm, more information available, less asymmetry), price-earnings ratio (higher ratio = higher growth potential but with higher uncertainty), industry of operation, and whether the firm is venture capital backed (reduced uncertainty due to previous valuation). The model also focuses on issue-specific factors, mentioning offering method and year of offer (for market frequency related trends – hot/cold market). This sets a base for our empirical model, providing control factors to help us isolate the effect of ESG classes on IPO underpricing.

Looking at further research conducted by Baker et al. (2021) to identify newer control factors for underpricing, we find the rank of the underwriter, offer size, gross spread, and stock exchange of listing to be relevant for our analysis. Given that we plan to conduct our analysis on regional samples, these factors level the other differences in our IPOs that may exist apart from its ESG alignment.

2.2. ESG and Firm performance

A pertinent and widely used example of the effect of ESG factors on financial performance is the pricing of "sin" stocks. The prevalence of social norms that deem firms that are in the industry of producing / marketing alcohol, tobacco, and other sinful products as immoral, has forced the stocks of these firms to be shunned and thus held by fewer people (Hong & Kacperczyk, 2009). This results in higher returns on such stocks, but comparatively lower coverage and greater risk. This phenomenon is interesting to understand as it builds into our question of ESG sentiment in the market, and how rational investor decisions may be overridden. Investors in such cases are willing to forgo profit and the advantage of diversification, therefore changing the previously understood investment/pricing model.

Similarly, ESG factors impact the decision-making of large institutional investors as well. As discussed by Saunter and Starks (2021), Pension funds are wary of investing in ESG-risk exposed stocks given their long-term horizon and the subsequent downside risk they must face. With their goal of wealth protection, pension funds modify their investment criteria to exclude firms with severe exposure to negative ESG events such as climate risk, in order to remove the possibility of underfunding its liabilities. As a result, the firms lose potentially large investments, and are forced to revalue their firm while raising funds to accommodate this opportunity cost.

On the other hand, Baier et al. (2020) show that as investors become more aware of Responsible Investing related to ESG, efforts taken by the firms for CSR practices and ESG disclosure is increasing. This is measured by the increase in ESG related communication is firms' annual reports, currently at around 4% of the word count of the report in the data sample considered. This reaffirms that firms listen to market sentiment and respond accordingly to meet investor expectations for sustainability. The method of measurement i.e. textual analysis is also noted as a suitable means of quantifying ESG efforts, which can be used to develop an ESG classification model (based on scores) for the analysis of our research question. However, the disadvantage of the method being time-consuming will have to be considered.

Further, when such ESG disclosure is mandated, the quality and availability information increasing drastically, and the cost to investors reduces as they do not have to rely on third parties to source this information (Krueger et al., 2021). This also leads to more accurate analyst forecasts and reduces uncertainty over stock price crashes. Finally, firms become more responsible in this scenario, actively avoiding negative incidents that effect firm operations and damage its ESG reputation.

As a whole, we see that ESG practices and disclosure ease uncertainty on investors and provide better access to funds for firms.

2.3. ESG and IPO performance

Huang et al. (2019) discuss the market effect of CSR disclosures by looking at the IPO's stock performance after a thirty-day period. Finding a positive relation, the authors further conclude that shareholding ratios for institutional investors are significantly greater with CSR disclosures. Reber et al. (2021) further discuss aftermarket performance of IPOs with reference to ESG disclosure and idiosyncratic risk in a one-year period. The study finds a negative relationship between disclosure and stock volatility, supporting the claim that ESG communication during IPOs greatly reduces informational asymmetry and downside risk. Building on these articles, we wish to understand if studies have been conducted on immediate IPO performance i.e. addressing the impact of ESG disclosure on pre-IPO pricing decisions and the subsequent underpricing level.

A widespread problem in such an analysis is the lack of readily available scores/measures that capture ESG alignment of firms for investors. A study by Baker et al. (2021) introduce an association between IPO underpricing and ESG factors at a country-level by utilizing MSCI's ESG ratings assigned to the firm's government as a proxy for the firm's individual rating. This assumption ties to our discussion above at *2.2. ESG and Firm Performance* (Krueger et al., 2021) where government ESG practices influence firm efforts. The study finds that countries with higher ratings have lower underpricing levels; where the effect is magnified in countries with higher transparency, mandatory disclosures, and more ESG risk management regulations. Alternatively, Boulton et al. (2010) find that countries with stronger corporate governance systems have higher underpricing on account of control motivation, where underpricing is a cost borne by insiders to maintain control in the post-IPO ownership dispersion (caused by higher demand). This large dispersion of outsider ownership will reduce the incentive for investors to monitor the firm's operations, thereby allowing for private benefits of control for insiders. Given our planned sample selection criteria, we assume that control motivation does not significantly apply to our dataset.

Another solution for this problem is to tackle ESG factors individually, and substitute firm metrics (such as board size, CO2 emission level etc.) for scores. Gonzalez et al. (2019) focus on the impact of Governance and tone of communication on IPO underpricing primarily. The article sources information from the IPO prospectuses of the firms, mimicking the situation of a regular investor. The study finds that an independent board correlates to lower underpricing due to reduced governance risk, whereas the more unconventional factor i.e. tone leads to higher underpricing when it is uncertain. Nevertheless, these results follow the general conclusion shared by all previous literature discussed above where lower information asymmetry reduces underpricing levels.

Some articles also suggest textual analysis as a method of accounting for ESG. Under this method, the frequency of usage of a defined list of ESG-related words in an IPO document is measured. This acts as a proxy for the ESG alignment of the firm. Fenili and Raimondo (2021) conclude that greater disclosure in the S-1 prospectus of U.S. IPOs is related to lower information asymmetry and hence lower underpricing. The study further shows the individual impact of each ESG factor, with ESG as a combined variable having the greatest effect, followed by governance and social factors. This is an important layered conclusion to reflect on which may give deeper insight into our research question as well.

From the above review, we find that textual analysis is the closest proxy for firm-level ESG factors discussed in underpricing models. However, this method has its drawbacks owing to its process where individual words are taken out of context and force fed into different categories where they otherwise may not belong. This reduces the legitimacy of the ESG proxy created and the resulting conclusions may ignore or underestimate parts of the information communicated.

With our research question and methodology, we aim to look into the impact of firm-level ESG factors on IPO underpricing, while addressing the methodical discrepancy of textual analysis by utilizing quantitative ESG scores instead of the above proxy. Further, we find that current research concludes on the impact of ESG as a binomial factor i.e. whether the prevalence of ESG practices/disclosure impacts underpricing, whereas in our detailed analysis, we will discuss if there is any difference that investors perceive between various levels of ESG involvement by classifying firms based on the above mentioned scores. Our conclusion will thus help researchers in this topic understand if the degree of ESG prevalence has an impact on investor sentiment and expectations.

3. Hypothesis and methodology

This chapter aims to illustrate the process in which the empirical research is conducted, specifically, the relationship between the level of ESG inherent in a firm and its level of underpricing. We begin by developing our hypothesis in detail and highlighting the variables we wish to test and analyze.

3.1. Hypothesis 1: ESG alignment

Our research question is:

"To what extent does IPO underpricing differ between classes of ESG firms?"

We define underpricing as the percentage difference between the offer price and the first-day closing price of the firm during its IPO. This difference is caused by several quantifiable factors, with varying degrees of significance, but also includes the abstract ideology of reward for information asymmetry. Following this line of thinking, firms underprice their shares so as to incentivise potential investors to participate in their IPO. This is driven by the acknowledgement that outsider investors hold much less information about the company's viability, prospects, and opportunities than the company's internal stakeholders. Additionally, it can also entail that this information is hard to gather or price by a non-institutional investors due to resource constraints, or simple lack of interest in exerting effort to do so. Given this, firms are forced to lower their valuation to match market expectations.

However, when we consider ESG efforts, we understand that the primary goal of these initiatives is to increase transparency and trust. For a firm, investments in ESG and awareness building can provide invaluable opportunities to disclose key business information to investors in relation to its operations and long-term vision. Knowing that ESG disclosures reduce information asymmetry between the two IPO parties (Baker et al., 2021), firms can liberally value their offerings to match their internal estimates. Firms reflect the fact that investors are now willing to pay more for the company's shares in their offer prices, thereby reducing a portion of underpricing experienced at the end of their first day of trading.

Our first hypothesis thus follows that:

A firm that undertakes ESG efforts is likely to have lower underpricing on its IPO than firms that do not participate in such initiatives.

This entails that we build a dataset of IPOs where we observe the underpricing for firms regardless of their ESG alignment. We further characterize these observations through a general dummy that captures whether a given firm undertakes ESG initiatives or not. If we code this factor as a dummy variable, with 1 representing a firm that takes ESG efforts, then we expect to see a significant negative coefficient for this dummy in our analysis, after controlling for firm-level underpricing factors. We have

$$Y_{underpricing\_i} = \alpha + \beta_1 ESG\_dummy_i + \beta_j X_{ji} + \varepsilon_i \quad (1)$$

where X_j denotes a set of control factors for underpricing (including *Country*) that will be detailed later and β_1 captures the effect of a firm that takes ESG efforts.

We choose to estimate our model using Ordinary Least Squares (OLS) multiple regression method, as it best fits our requirement for unbiased estimators in a complicated setting with dummy variables and potential interaction effects. The drawbacks and caution points of this method, primarily its strict assumptions, will have to be kept in mind during our analysis. Appropriate tests for assumption violations will be conducted on our dataset to check the suitability and robustness of the methodology.

This hypothesis can be seen as an extension of the results presented by Fenili and Raimondo (2021) as discussed in *2.3. ESG and IPO performance*, where we substitute the use of textual analysis with quantitative data analysis that uses a firm's calculated ESG score as a proxy of its ESG alignment instead of its qualitative disclosures in regulatory filings.

3.2. ESG Scoring

Our model detailed in Eq (1) warrants the use of a dummy variable that captures whether a firm undertakes ESG efforts. As referenced by previous literature, it is difficult to quantify ESG alignment of a firm due to several reasons that include lack of information, absence of standardized ESG reporting procedures, and limited availability of analysts and data aggregators that specialise in ESG disclosures. However, in recent years, few data providers such as Refinitiv Eikon and Sustainalytics have begun to publish ESG data on listed firms that are gathered through all publicly available reports shared by the companies. These organisations also consolidate the ESG data gathered to build scores that reflect a firm's ESG efforts of a fixed scale, allowing researchers to analyse and compare their ESG variables of interest across firms.

Our preliminary strategy for this research question is to develop our own ESG score based on important themes across ESG pillars. This method will entail numerous hours of data logging, might be subject to information scarcity due to lack of resources, and potential human errors in compiling the data. It is also important to consider the quality of contribution to research when the time frame of a Master Thesis project can only accommodate a basic model. Furthermore, the platforms that offer some of the base ESG information we wish to gather such as Refinitiv, already use the ESG data they provide to build detailed scores as mentioned above. Hence, given that the true scope of this paper is to understand the effect of ESG efforts on underpricing, and not to introduce a ESG quantifying model to research, we choose to utilize the scores developed by Refinitiv for our dataset.

We now look further into Refinitiv's methodology for ESG scoring. We find that the platform hosts real-time and accurate ESG information for a large set of companies across the globe, and uses the 450+ metrics that it captures to build a detailed ESG profile of a given firm (Refinitiv, 2021).

Refinitiv's Materiality matrix divides ESG pillars into themes such as resource usage/wastage, emission, human rights, working conditions, transparency, board diversity and structure etc. For each theme, there are quantitative data points that can be sourced from the Eikon database. An individual score is calculated for each data point (value) as follows

$$\text{Data point score} = \frac{Firms\ in\ the\ industry\ that\ have\ worse\ value + 0.5}{Total\ number\ of\ valued\ firms\ in\ industry} \qquad (2)$$

Where the 0.5 is for error correction, and "valued firms" indicate firms considered in our dataset that have a numeric value for the data point (not empty). Dummy variable data points (yes/no) are considered as is without a score conversion.

These individual scores are then combined to form scores for their respective pillars (E, S and G), after which they are weighed by a standard weights matrix (based on the industry) provided by Refinitiv to generate a combined ESG score. These scores range from 0 to 100, which are further translated into a 12-point grading scale ranging from A+ to D-, for each score/datapoint considered.

The metrics used for the pillar scores are determined based on pertinent UN Sustainable Development Goals (SDG) themes, along with Refinitiv's own research on other material factors in the ESG bubble that have long-term impact. These scores and metrics are also personalised for each industry, to reflect clustering on an aggregate level. As the relative scoring methodology entails the comparison of a firm's ESG performance against all other firms in its industry, scores are more meaningful and localised.

In our analysis, we take firms that have a Refinitiv ESG score to be a part of the *1.ESG_dummy* category i.e. firms that take ESG efforts. We understand that some firms may not disclose their ESG efforts due to various reasons, while others might not have been accounted for on the Refinitiv platform, thereby not having a score. Given that research on the relationship between ESG disclosure and information asymmetry is reasonably established in recent literature (Baier et al., 2020; Gonzalez et al., 2019), we assume that a company which wishes to reap the benefits of ESG disclosure – irrespective of the level of ESG efforts – for lower information asymmetry will prioritize the publication and communication of its ESG efforts. This assures us that any categorization bias with omitted firms will be partly justified and negligible in our analysis.

It is also important to mention that given our planned time period for the analysis, firms with IPOs in the early years before the widespread publication of Refinitiv ESG scores might not have a score at the time of their IPO. For this, we broadly assume that the nature of a company and its operations does not drastically change across a given time period with all things constant – in the absence of restructuring or other unusual corporate events. With this, the average ESG score and alignment of a company can be assumed to be constant over our timeframe. In further sections of this paper, we hope to run robustness tests for this assumption with our final dataset.

3.3. Hypothesis 2: Classes of ESG Firms

With an established model and hypothesis to capture the binary effect of ESG adoption in firms, the next step of interest is to analyse underpricing across the class of ESG firms we identify. The purpose of this hypothesis, which forms the crux of our analysis, is to provide insight into a firm's decision-making when it has an inherently high/low class of ESG in terms of underpricing i.e. its offer price, and the subsequent understanding of market efficiency and the adjustment that takes place relative to its decision.

We begin with a hypothesis such that

A firm that belongs to a high ESG class is likely to have lower underpricing on its IPO than firms that belong to lower ESG classes.

This hypothesis supports that a firm acknowledges its ESG efforts and the subsequent potential for reduced information asymmetry, and increases its offer price (i.e. realises lower underpricing) under the theory that investors assimilate the information provided and adjust their valuations to more closely match the firm's own estimates/potential.

To test our hypothesis, we use the 12-point ESG grade segregation defined in *3.2. ESG Scoring*. We consolidate these grades into classes at intervals of 20 datapoints (3 grades), where a lower score/class indicates poor ESG performance. We thus have 4 classes of firms that reflect the firms' inherent ESG level/efforts ranging from *C1* to *C4*, with *C1* being a Class 1 ESG firm of the highest level.

$$Y_{underpricing\_i} = \alpha + \beta_1 \, ESG\_dummy_i + \beta_2 \, ESG\_class1_i + \beta_3 \, ESG\_class2_i + \\ + \beta_4 \, ESG\_class3_i + \beta_j \, X_{ji} + \varepsilon_i \quad (3)$$

It follows that more disclosure – linked to a higher ESG class – leads to greater reduction in information asymmetry. Hence, a C1 firm is likely to have lower underpricing than a C2/C3/C4 firm; an effect that we analyse using dummy variables with C4 as our reference group. The same relative hypothesis applies to other classes of ESG firms. In our regression analysis, we expect the ESG class dummies to have a significantly negative coefficient in determining underpricing.

Similar to the methodology used for classifying the consolidated ESG scores of firms, we can extend our analysis to model the impact of separate E/S/G pillar scores with the same class segregation (E1 – E4, S1-S4…). This will allow us to understand if the hypothesized relationship between underpricing and ESG efforts differs for each of its pillars.

We now note that in our analysis of the above hypotheses, there is a potential selection bias which might hamper our results while using OLS. The structure of the hypothesis is such that it only considers a subsample of our dataset, i.e. firms that have an ESG score, which can then be classified into levels to use in our analysis. In this situation, firms without scores are not represented in the sample, and our results become biased. This would also affect the fit of the OLS model, causing it to be tailored to predict underpricing for firms similar to the ones on our dataset, rendering it problematic for further applications and robustness tests.

3.4. Selection bias

Selection bias occurs in models where the sample selection is not random. A widely discussed example of such a problem is the analysis of hourly wage distribution and the issue that women choose to participate in the labour market, but this choice is not random. Hence the sample considered is biased as participants self-select into it (Heckman, 1976).

In our analysis, we face a problem where we consider a non-random subsample of our dataset that fits our criteria of having firms with ESG score that can then be classified into different levels. Hence, there is a potential bias present which we need to test for and resolve.

In the usual Heckman two-step model, the analysis is split into two equations that are estimated simultaneously to remove the self-selection bias. Here, a selection model (Level 1) with variables that potentially explain the probability of selecting into a subsample is embedded in the main regression (Level 2 equation). The simultaneous estimation creates a correction for the bias, allowing us to run the main regression using OLS with an added covariate.

However, an important feature of the applicability of the Heckman model is the model assumes that the dependent variable can only be observed for certain values of the independent variable (values of the *treated*). Comparing this to our selection issue, we find that we observe *y* i.e. underpricing for all observations in our dataset, but our sample selects itself based on values of an independent variables, namely

ESG_dummy i.e. the variable that captures if a firm has an ESG score available. In this case, the Heckman model is not suitable for our analysis and we must adopt other established methods to overcome the bias.

We look at an *endogenous treatment-variable regression* method which is an extension of the Heckman selection model to accommodate for the difference in problem statement (Cameron and Trivedi, 2005). The methodology is similar to other selection models, where bias is caused by endogeneity and Heckman-type corrections are applied using a control function approach (Heckman, 1980; Heckman and Robb, 1985). In this methodology, we estimate Average Treatment Effects (ATE) which approximates to the value added to an outcome when the variable undergoes "treatment" compared to not doing so. If such a treatment effect is significant and the expected mean difference between the treatment and non-treatment group is not equal to zero, then the treatment is said to be effective and to have a significantly different effect on the outcome than the reference group.

Relating the above to our analysis, we can use treatment effects to estimate if the value of underpricing (outcome) is different for ESG firms (treatment group) compared to the subsample we cannot consider i.e. non-ESG classified firms. Running the above control function approach model will allow us to capture this effect and result in unbiased estimates if such a selection bias exists.

We thus specify our integrated model as follows:

$$Y_{underpricing\_i} = \alpha + \theta_1\, ESG\_dummy_i + \beta_1\, ESG\_class1_i + \beta_2\, ESG\_class2_i + $$
$$+ \beta_3\, ESG\_class3_i + \beta_j\, X_{ji} + \varepsilon_i \quad (4)$$

$$ESG\_dummy_i = \alpha + \beta_1 lnFirmsize_i + \beta_2\, FirmAge_i + \beta_3\, CSRreporting\_dummy_i +$$
$$+ \beta_j Country_{ji} + \beta_k Industry_{ki} + \varepsilon_i \quad (5)$$

Where Eq (4) refers to our main underpricing model, corrected for selection bias using a selection equation defined for the ESG_dummy variable in Eq (5).

For our control function, we use the variable *ln_FirmSize* which is a natural log transformation of the total assets of a firm before its IPO. This variable helps us control for the size effect attributed to firms where larger companies have greater resources to dedicate to ESG efforts and coverage, thereby increasing the probability of having an ESG score (Drempetic et al., 2019). *Firm age* accounts for the information availability problem, under the hypothesis that older firms tend to have more historical data from which one can derive and consolidate ESG information. Country and Industry dummies are included to account for the differences in ESG alignment within each category of the variables. The country dummy captures the effect of country-level ESG mandates and ESG performance and its impact on a firm and its ESG efforts (Baker et al., 2021). Finally, a dummy for whether the firm has CSR reporting is used to understand if a firm voluntarily participates in any type of ESG disclosure (without a mandate, where CSR reporting is taken as a proxy as it is the most well-known ESG disclosure type).

The control function approach will be executed in *Stata*, where the model specifications assume normality, independence, and equal variance of error terms. An important assumption is that the error terms of the main regression and selection model are bivariate normal, and their correlation i.e. rho (ρ) indicates the level of selection bias present in the model (Cuddeback et al., 2004).

Although this integrative model estimates and corrects for selection bias as hypothesized in our analysis, such models have limitations as well. As the approach requires us to build a subjective control function, the usefulness of the model depends on how well we define the variables that capture whether a firm has an ESG score or not. This may impact the effectiveness of the model in correcting for bias, and may affect estimates of our main regression model, thereby skewing results. As our selection variable *ESG_dummy* is fairly straightforward, we assume that our control variables capture enough of the effects to avoid large errors.

3.5. Regression variables

With our established base models and hypotheses, we now begin to define the control variables to be used in our underpricing regression. Numerous researchers have published past literature in the pursuit of determining factors and variables that would affect the level of IPO underpricing. By aggregating this wide range of literature, industry researchers have come to agree upon specific determinants which in fact appears to have significant explanatory power on the level of underpricing, including certain firm characteristics such as firm age and industry, as well as IPO characteristic variables such as offer size, underwriter rank and green shoe options (Ritter, 1984; Beatty & Ritter, 1986).

3.5.1. Dependent variable – underpricing

Underpricing is the dependent variable of the regression model, as the study is aimed towards researching whether the level of underpricing can be explained by the level of ESG inherent in firm. Underpricing is defined as following:

$$Underpricing = \frac{Closing\ Price - Offer\ Price}{Offer\ Price} * 100 \tag{6}$$

The underpricing variable aims to express in percentage terms how much a stock appreciates or depreciates during its first day of trading in public. The offer price is the price in which shares are sold in the initial public offering prior to the listing and subsequent trading on a public stock exchange. The closing price portrays the final price at which the stock traded on its first trading day. Hence, underpricing is defined as *"the percentage change from the offer price to the market price at the end of the stock's first trading day"* (Dolvin, 2012).

3.5.2. Independent variables – control factors

Following the literature detailed above, we estimate the need for the following underpricing control variables to accurately model our base regression:

3.5.2.1. Firm-level factors

Firm age

The firm age, or maturity, is considered the most significant variable when researching underpricing. Ritter (1984) suggests that the firm age could be the proxy for "difficulty of firm valuation". Mature firms naturally have a larger amount of historical data, contributing to the both the ease and accuracy of valuation. Consequently, valuation conducted by industry analysts tend to follow a narrow range, as the large amount of historical data contributes to a valuation in which is commonly agreed upon. Conversely, younger firms have less historical data to use as reference points in valuation and are therefore subject to a wider valuation range among industry analysts. This can be explained by the fact that valuation of young firms with limited historical data requires a higher number of subjective assumptions, which consequently results in disagreement of valuation among industry analysts. With analysts, investors and underwriters having significantly different opinions about a firm's intrinsic value, underpricing may be larger due to wide gaps between offer price and perceived intrinsic value.

Firm age is calculated as the difference between the year of IPO and year of incorporation of the specified company.

Firm size

Firm size is a widely use control factor for IPO underpricing as it captures the important implication that markets have more information on larger firms (Rock, 1986; Welch, 1989). This hypothesis supports that investors are better informed on the operations and prospects of larger firms participating in IPOs, and thereby have more accurate valuations on these firms owing to reduced information asymmetry. Studies on IPO underpricing thus find that a large firm generally observes a negative relationship between its size and the level of underpricing on its new issue (Mauer and Senbet, 1992).

For our analysis, we take the total assets of a firm before its IPO as a proxy for firm size. To normalize the distribution of these values, we transform the data using natural logs.

Industry

The industry in which a firm operates in could reveal a number of its characteristics, hence its importance in researching IPO underpricing. Industry literature on the topic of IPOs portrays high underpricing return tendencies particularly from industries described as high technology industries, which comprises of computer equipment, computer software, biotech, electronics, and general technology. Lowry & Schwert (2002) and Loughran & Ritter (2002) thereby find that IPOs of high technology firms experience higher first-day returns relative to that of other industries. This can be explained by the suggestion that high technology firms are considered riskier, as the value of such firms are largely derived from future growth options as opposed to tangible assets (Lowry & Murphy, 2007; Lowry et al., 2010; Lowry & Shu, 2002). The high volatility inherent in riskier stocks might therefore explain larger first-day returns. Furthermore, with reference to the section above, firms of which value are derived from future growth options may be more difficult to valuate as the valuation requires more subjective assumptions to be made. Thus, investors may disagree on the offer price, causing large price movements during the first trading day.

In addition to its standalone impact, the industry dummy also helps us test our ESG hypothesis. We can expect on general merit that firms within the renewable energy industry have higher ESG alignment than other industries such as industrials or real estate. With this understanding of each industry's overall ESG theme, we can support our findings on IPO underpricing at a firm-level with its industry-level performance.

In our analysis, firms will be classified into industries based on their TRBC (The Refinitiv Business Classification) economic sector, with one of 13 values, which are modeled after the widely accepted Global Industry Classification Standard (GICS) developed by Standard & Poor's in 1999.

Venture capital backing

Venture capital financing is a form of private equity financing, typically provided as seed or early-stage capital to startup companies. Megginson and Weiss (1991) argue that whether or not a firm has been financed by venture capital may affect its IPO in the context that venture capitalists provide a contribution to the firm's transparency when it goes public. As such, venture capitalists may contribute to reduce information asymmetry. Furthermore, venture capitalists' knowledge about a firm may be helpful for underwriters conducting valuation for the purpose of pricing the offer, thus reducing the extent of the book-building process.

Bradley and Jordan (2002) insinuate that the typical characteristics of a venture-backed firm give substance to the suggestion of higher first-day returns post-IPO. This argument builds on the assumption that venture capitalists tend to invest in risky startups whose value is derived from future growth options. As such, companies who are typically regarded to be targets for venture capital financing tend to be more difficult to valuate due to their firm- and industry specific characteristics – pointing in the direction towards higher first-day returns. We make a distinction here between the opposing theories, and proceed with our analysis of determining the effect of a firm receiving venture capital financing on its IPO underpricing by treating the factor as a dummy variable.

3.5.2.2. Market-level factors

Country

As we aim to build a cross-sectional dataset that spans important regions namely the United States and the Nordics i.e. Norway, Sweden, and Denmark, we control for the general effects of each country on the average underpricing level observed for firms within its region. Including these factors as dummy variables in our analysis will allow us to build our regression model and interpret the impact of each explanatory variable without any bias caused by observation clustering at a hierarchical level.

Our base research extends to studying potential differences in the market sentiment for ESG across these geographical regions, or markets. More specifically, we aim to study whether there is a difference between the stock markets in the Nordics and the US. Literature portrays that Nordic countries tend to place a higher importance on ESG considerations. We therefore expect to observe a trend in which the demand for high-ESG issues is elevated, implying a market adjustment for ESG. As such, we expect larger underpricing for high-ESG issues in the Nordic markets. Additionally, the Nordics are involved in European initiatives such as the EU Taxonomy as well as being exposed to the European Union's enforcement of environmental, social and governance regulations – all of which reflect the relatively high importance of ESG in the European area.

Stock exchange

The stock exchange in which shares are listed may impact the level of IPO underpricing due to a variation of reasons. In this context, we assume two types of stock exchanges per country of listing – specifically, one stock exchange which lists large-cap stocks and another which lists small-cap stocks. Stock exchanges which list large-cap stocks typically impose extensive formal requirements upon the companies listed on such stock exchange. Consequently, only a certain number of firms qualify for listing on these more traditional stock exchanges – typically comprising of mature companies of larger size. Younger and smaller firms who do not meet such formal requirements may consequently choose to offer their shares on less-regulated stock exchanges such as Nasdaq. Listing on such stock exchanges is more cost-efficient, as listing fees are lower relative to more traditional stock exchanges such as NYSE in the US. Consequently, listings on Nasdaq and equivalent stock exchanges typically comprise of younger, smaller, and more growth-oriented firms. A common denominator for these firms is therefore difficulty of valuation due to their characteristics as discussed in section *3.5.2.1 Firm-level factors*. Thus, initial public offerings on Nasdaq or equivalent stock exchanges are expected to experience larger underpricing.

Across the regions considered, we take NYSE in the US, Oslo Bors in Norway, and Nasdaq Main in Sweden and Denmark to be large-cap comparable stock exchanges. The other category of exchanges is characterized by small-scale growth firms and are namely Nasdaq in the US, Euronext in Norway, and Nasdaq First North in Sweden and Denmark.

Year of IPO

The year of issue is an important control variable as it places the IPO in the context of its current market in terms of IPO activity. A widely discussed term in IPO studies is the "hot-issue" market, characterized by significant levels of IPO activity in a given time frame (Ritter, 1984). Including year dummies in our analysis will allow us to control for these effects and understand the relevance of timing of issues, and give us an insight into the factors influencing decision-making that precede a firm's new issue.

The year factor also allows use to build upon ESG hypothesis, by indicating periods of high ESG demand in the market. With the advent of several ESG movements across the years that have increased investor and firm awareness on the materiality of ESG, it is important to chart the effect of events across our multi-year dataset. As an example, following the Paris Climate agreement, global financial markets saw high fluctuations in the shares of ESG-controversial companies such as Exxon Mobil, which was driven by investor demand for ESG efforts, and the subsequent market adjustment for such preference (Reuters, 2021). Although a long-term trend in modified investor preferences is still to be observed, it is intuitive to assume that the calendar on such events has at least a pronounced short-term impact, making it vital to analyse in our understanding of underpricing in the IPO market.

Market Return

In IPO studies, underpricing is seen to be higher when overall market return is high (Ritter, 1984). This correlates with the market timing hypothesis that firms plan their issues on markets to take advantage of the high valuations that are possible with current rates, compared to the book value of their offerings (Baker and Wurgler, 2002). Strong market return is complemented by high demand, which decreases the cost of equity for issuers, thereby incentivizing companies to go public. Along with the year dummy variable, market return captures the combined hot-market effect (Boulton et al., 2010).

To measure this variable, we take the average market return for the year on prominent market indices that follow each region considered.

3.5.2.3. IPO characteristics

Offer Size

The offer size of an initial public offering is the gross amount raised by a company by issuing new shares to the public. The difficulty of valuation thereby decreases as the offer size increases (Carter et al., 1998). As such, Beatty and Ritter (1986) argue that smaller offers appear to be more speculative and thus subject to larger underpricing. This argument follows the rationale that more mature and established firms, typically one raising more money, are easier to valuate and thus the valuation opinions of analysts follow a narrow range However, given that we cannot establish a proven connection between offer size and firm size for a localized dataset in the absence of detailed quantitative analysis, we include both variables in our regression model to account for their separate effects, given collinearity does not exist. Provided that the offer price lies within this narrow valuation range, offerings of larger sizes are thus expected to experience lower underpricing than that of smaller sizes.

We expect to use natural log transformations on the observed values for this variable to normalize the distribution and results.

Underwriter rank

The involvement of high-reputational underwriters can reduce uncertainty and thus first-day returns by certifying an IPO (Baker et al., 2021). However, the evidence found in studies conducted on the relationship between underwriter reputation and IPO underpricing is mixed. The first viewpoint is the outcome of early research conducted by Carter and Manaster (1990) and Megginson and Weiss (1991), where evidence implies that IPOs involving prestigious underwriters are associated with lower underpricing. This viewpoint follows the argument that high-reputational underwriters reduce uncertainty by certifying an IPO, where investors do not demand a higher discount on its price. On the contrary, Beatty and Welch (1996) and Loughran and Ritter (2002) argue that underpricing is positively correlated with underwriter reputation since early research. This evidence may insinuate that prestigious underwriters intentionally set the offer price below the intrinsic valuation in order to preserve the relationship with their clients and investors. By setting the price below fair valuation, underwriters ensure underpricing for their clients, provided that the markets are efficient and that mean reversion is present, i.e. that markets will correct the price until it approaches its intrinsic value.

In the context of our research, the underwriter rank variable is defined on a scale of 0 to 5 according to independent, published rankings. For US IPOs, we consult the rankings put forth periodically by Carter and Manaster, which have been referenced by several underpricing studies. For the Nordics, we refer to the rankings published by Kantar Sifo, a Swedish research company that shares annual rankings of top underwriters in the Nordics on a 5-point scale. The proposed methodology for US underwriter ranks gives us a score on a 9-point scale with a score of 8/9 being classified as high. We standardize these rankings to a 5-point scale to match the measurement for Nordic companies.

The underwriter of highest reputation is ranked the highest at 5. The lowest rank of 0 is reserved for IPOs that are managed by underwriters who are not included in the rankings due to their limited reputation and prestige. Furthermore, the variable is country-adjusted to absorb differences in underwriter rankings across countries.

Green shoe percentage

Green shoe refers to an over-allotment option given by the issuer to underwriters, where if the IPO experiences high demand, the underwriters can exercise this option to buy additional shares from the issuer at no additional cost to meet such increased demand (Chung et al., 2000). This option can be exercised for up to 15% of the initial shares offered, but can vary between individual IPOs. The primary goal of this option to allow underwriters to meet any unforeseen demand, while also ensuring price stability and after-market liquidity.

However, a potential misalignment of incentives may occur when underwriters willingly underprice shares in an effort to profit from the over-allotment option when market demand exceeds the number of shares allotted for the IPO. The existence of such an option can also be correlated with an artificial demand for the shares, as investors might perceive the IPO to be highly lucrative if issuers / underwriters believe the issue is undervalued.

We not only wish to look at whether an over-allotment option exists and affects IPO underpricing in our dataset, but also hope to understand the relationship between the level of underpricing and the percentage of over-allotment exercised during an IPO period.

Gross spread

Gross spread refers to the total fees paid to underwriters in an IPO, expressed as a percentage of offer size. In a new issue setting, underwriters have incentives to price shares higher than their fair value estimates as the direct fees paid by the issuing firm is dependent on the gross proceeds of the issue. These spreads do not usually change even when issue proceeds are revised (Chen and Ritter, 2000). However, underwriters may be inclined to underprice IPO shares so as to receive a form of "indirect compensation" where they can appease larger investors who wish to buy at lower prices, or where they stand to benefit from exercising a green shoe option, allowing them to increase their profits. Here, the gross spread can be seen as a control variable in explaining underwriter motivation in relation to a dual revenue-generating strategy. However, this hypothesis cannot be effectively tested in our regression.

Pricing technique

The method by which IPOs are priced differ between individual IPOs and also regions considered. Bookbuilding is the most widely used pricing method globally, where issuers specify a range of values within which the final IPO price is decided based on a weighted average of the demand / bids for each price in the range. Bookbuilding is hypothesized to result in lower underpricing for IPOs compared to fixed price deals (Sherman, 2005). However, studies show that this effect is primarily observed only in US markets, or when an international IPO has US investors or underwriters (Ljungqvist et al, 2003). Overall, the general consensus from literature on this variable is that it is a significant factor in underpricing studies.

4. Data and preliminary analysis

To test our hypotheses set out in section 3, we build a cross-sectional dataset of IPOs that have occurred between the years 2014 and 2021 (until June 2021). The data will focus on two broad regions namely the United States and the Nordics market, defined by the countries of Norway, Sweden and Denmark. We find that IPOs in Finland are sparse and do not have comprehensive and standardized global reporting, making them difficult to include in our dataset. On the other hand, Norway, Sweden, and Denmark are highly active international markets for equity offerings and provide a comparable set of firms for our analysis against US IPOs.

We begin by gathering a list of IPOs that have taken place within our timeframe by looking at SEC filings for the US, and individual stock exchange data for each Nordic submarket. The ISINs sourced from this preliminary data collection are subsequently matched to equity deals on the Refinitiv database to source further information on IPO-, Firm-, and market-level variables. We begin with 2295 observations for the US and 460 for the Nordics region. With this draft, we look to eliminate any firms or deals that do not fit our definition of Initial Public Offerings such as SPACs, direct listings, or shell companies. Additionally, information availability that is impaired due to subsequent delisting or non-disclosure is dealt with by elimination as well. Any bias caused by the last step is considered to be negligible as the eliminated group forms less than 10% of the original dataset. We conclude on our list with 1676 US IPOs and 322 Nordic IPOs.

Table 1: Distribution of IPOs by country and stock exchange type

Country	Large cap SE	Small cap SE	Total	Percent	Cum.	SE dist.
Denmark	13	28	41	2.05	2.05	
Norway	34	95	129	6.46	8.51	
Sweden	67	85	152	7.61	16.12	
USA	523	1153	1676	83.88	100.00	
Total	**637**	**1361**	**1998**	**100.00**		

Large cap SE: Nasdaq Copenhagen, Oslo Bors, Nasdaq Stockholm, NYSE
Small cap SE: Nasdaq First North Denmark, Euronext, Nasdaq First North Sweden, Nasdaq

Data on ESG scores for the sample is collected from Refinitiv. Along with combined ESG scores that form the base of our analysis, we source individual pillar scores for Environmental, Social, Governance to augment our models. Within our dataset, 897 firms have an ESG score on the Refinitiv platform, 781 of which are US IPOs. The distribution of ESG grades and the subsequent firm ESG classes are summarized in the below table.

Table 2: Distribution of ESG grades and classes by country

ESG Class	Grade	Denmark	Norway	Sweden	USA	Grade total	Class total
Class 1	A+	0	0	0	0	0	4
	A	0	0	2	0	2	
	A-	1	0	0	1	2	
Class 2	B+	0	2	3	9	14	107
	B	2	3	9	28	42	
	B-	1	3	8	39	51	
Class 3	C+	2	2	13	63	80	433
	C	0	4	11	133	148	
	C-	2	5	12	186	205	
Class 4	D+	2	0	11	201	214	353
	D	0	0	13	111	124	
	D-	0	1	4	10	15	
N/A	N/A	31	109	66	895	1,101	1,101
Total		**41**	**129**	**152**	**1676**	**1998**	**1998**

Table denotes count of IPOs under each category.
ESG class categories created by the authors for the sole purpose of this paper. Data source: Refinitiv

Values for most of the underpricing control factors considered in our model are available on Refinitiv. Continuous variables expressed in monetary terms have been standardized to US Dollars for comparability, converted at exchange rates prevailing at the end of the IPO quarter. These variables include offer price, closing price, offer size, overallotment amount, and total assets before offering. The defined dummy variables in our data are year of IPO, industry, country of listing, stock exchange of listing, pricing technique, underwriter name (used for dummy: rank), venture capital backing, and CSR reporting dummy. Other variables such as gross spread (individual) and market return (for each country/year), are sourced from Refinitiv as well.

We use data on the overallotment amount is used to calculate green shoe as a percentage of offer size. We also calculate firm age as the difference between the year of IPO and year of incorporation of the firm.

Additional sources for data include Morningstar company factsheets for information on total assets of Nordic IPOs, SEC data on Form 424B4 for US IPOs, S&P Global Market intelligence and Jay Ritter's IPO database for gross spread information, and EY Insights for information on IPO activity.

For our analysis, we split our sample into two so as to allow for future out-of-sample forecasting, if the regression model fit is deemed suitable for such purpose. We proceed with our in-sample data of IPOs between the years 2014-2020, consisting of 1479 observations across regions. The IPOs that occur in 2021 (until June 2021), 519 observations, become a part of our forecast sample.

4.1. Preliminary Analysis

We begin by listing our final variables for the regression models, and stating the proposed relationship we expect to see for each of these values against our dependent variable – underpricing.

Table 3: Regression variable description - Continuous

Variable	Function	UoM	Brief description	Expected relationship
Underpricing	DV	percent	Difference between offer price and closing price on the first trading day	---
Firm age	IV	---	Age of firm at the time of IPO	-
Firm size	IV	$ million	Total assets of firm pre-IPO	-
Offer size	IV	$ million	Size of IPO: offer price * shares offered	-
Market return	IV	percent	Average return on market index for given country and year	+
Gross spread	IV	percent	Underwriter fees as a percentage of Offer size	+/-
Greenshoe	IV	percent	Overallotment option as a percentage of Offer size	+

Note: Values denoted with "---" represent N/A

Table 4: Regression variable description - categorical

Dummy	No. of categories	Reference group	Brief description	Expected relationship
Industry	12	Academic services	TRBC industry classification	---
IPO Year	7	2014	Year of IPO as per issue date	---
Country	4	Denmark	Country of listing	---
Stock exc	10	Oslo Bors	Stock exchange of listing	---
Underwriter rank	6	0	Ranking of IPO underwriter on a scale of 1-5, with 5 as highest rank 0 for not ranked	+
VC backed	2	No	If firm received any previous Venture capital financing	+/-
Pricing technique	2	Fixed	Pricing method used for IPO: Bookbuilding and Fixed types	-
ESG_dummy	2	No	If firm has an ESG score available	-
Firm ESG class	4	Class 4	Categorical variable to measure firm's ESG level from Class 1 to Class 4	-
CSR reporting	2	No	Flag to capture if firm undertakes CSR reporting	-

Note: Values denoted with "---" represent N/A

The above table consolidates our hypotheses for each control factor as detailed in *section 3.5.2 Independent variables*, along with firm ESG class dummies that form the main part of our analysis. Following our regression analysis, we will also run tests to understand the joint significance of ESG classes and regions to tie into our research goals for this paper.

4.1.1 ESG score robustness

As mentioned in section *3.2. ESG scoring*, our analysis is based on the use of consolidated ESG scores from Refinitiv as a proxy for ESG efforts of a firm. Given the expanse of our dataset, it is likely that we do not observe ESG scores for firms at the exact time of their IPOs, especially for early observations in the years of 2014-2017. However, we believe that the core nature and operations of a firm do not change drastically within the time period of our dataset, hence post-IPO scores can be used as a substitute for hypothesized pre-IPO ESG alignment.

To test the robustness of this assumption, we take a subsample of our dataset where firms have ESG scores available before their respective IPOs. We analyze the spread of these scores and test to understand if they are stationary over time. If stationarity holds on average across the observations considered, then we conclude on its robust nature and proceed with our analysis given these substituted score values.

We collect data on the ESG scores of all firms in our dataset for the years 2012-2021. Filtering those that have an ESG score assigned at least during the year of IPO, we find a small sample of 25 firms. These observations have ESG scores for 1-4 years before their IPOs. Hence, building our model for stationarity tests, we have 25 individual time-series, with 7 periods (IPO+2, IPO+1, IPO, IPO-1,.., IPO-4). However, not all series have scores for each time-period. This severely limits our data for stationarity analysis, and traditional tests such as ADF or KPSS may not provide accurate results with these limitations (Arltova and Fedorova, 2016).

In this situation, we resort to simple graphical methods, where we visualize the data available and conclude on the appearance of stationarity / trend in values. The graph below shows the point ESG score on a scale of 0-100 for all observations in our sample across 7 time periods.

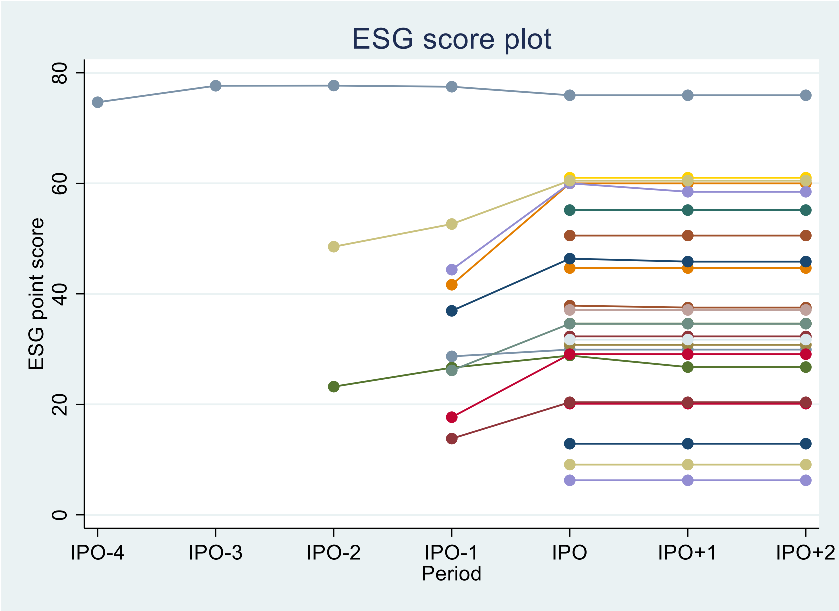

Figure 1: Connected plot of ESG point scores for subsample of IPOs across seven time periods

As seen, several observations lack data on strictly pre-IPO ESG scores. For firms that do have a score available, there is a slight increase in these scores during the year of IPO, presumably due to increased information availability. However, IPO year and post-IPO scores are consistent and appear constant across the three forward time periods.

It is important to note here that in our analysis we consider classes of ESG firms, instead of a continuous indicator such as the point score. Hence, looking at the variation in ESG class of these firms across the time periods would be more beneficial. However, as the condensation rate when we move from a continuous scale to four simple categories is high, we elect to choose an alternative where we look at the variation of the 12-point ESG letter grades instead.

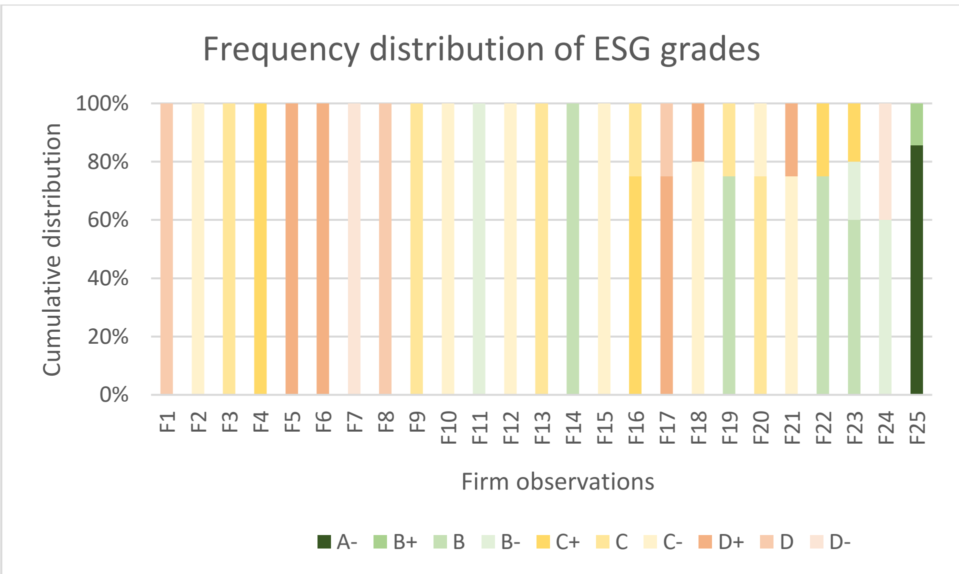

Figure 2: Distribution of ESG grades for subsample of IPOs across seven time periods

This shows that firms tend to stay within their ESG grade category on average across the time periods, despite having minor fluctuations in their point ESG scores. This ties into our hypothesis that ESG classes can be considered constant across our timeframe as core operations of a firm do not drastically change over a short span. We nevertheless acknowledge the subjectivity of our analysis and agree to be mindful of its implication while presenting our main results.

4.1.2. Descriptive statistics

To provide a better understanding of our dataset and the variables we consider for the regression analysis, we present the following summary statistics on our independent variables and discuss the implications of important parameters such as correlation and mean distribution.

Table 5: Descriptive statistics on continuous variables

Variable	**Obs**	**Mean**	**Std. dev.**	**Min**	**Max**
Underpricing	1,479	0.1511	0.3292	-0.9001	2.8370
Firm age	1,479	11.1954	15.5054	0	163
Log firm size	1,479	3.8086	3.0975	-3.6889	11.7774
Log offer size	1,479	4.6731	1.3745	-1.7042	9.9882
Gross spread	1,479	0.0574	0.0165	0.0025	0.1200
Green shoe pct	1,479	0.0846	0.0727	0.0000	0.2883
Market return	1,479	0.0463	0.0792	-0.3640	0.2250

The above table indicates a vast range of underpricing observed for our observations, despite controlling for outliers in our preliminary clean up of the data. However, this range is plausible given the different firm and IPO characteristics we are considering over a seven-year period. The lower bound for underpricing is negative, indicating that certain observations experience steep price drops from their offer price on the first day of trading. This phenomenon is valid and does not warrant exclusion.

We also build on the other continuous variables defined in *Table 3*. Primarily, when we look at the distribution of the variables *firm size* and *offer size*, we notice that the magnitude of these factors is vast (measured in $ million) and fitting their raw values against a lower-scale variable such as underpricing may be complicated. Hence, we compare the effects of natural log transformation on the distribution of these values, and conclude on the use of the transformed variables instead.

Figure 3: Distribution comparison of total assets and ln (total assets)

As seen above, the spread of the *total assets* variable is severely affected by outliers and an unbalanced upward distribution of raw values. Taking the natural log transformation allows us to fit the data into a better distribution, allowing for easier application in regression analysis and interpretation. We note here that taking the natural log of values less that one (i.e. one million in total assets) leads to negative values on transformed variable. The same interpretation follows for the *offer size* variable, where we also elect to transform its values in a similar way.

The descriptive statistics in *Table 5* include the transformed variables for firm and offer size, and display a much healthier range of values for these factors. The variable *firm age* is discrete in our dataset, and the summary shows that the average age of IPOs considered is around 11 years. However, the standard deviation on this variable is large and is possibly so due to large jumps in the ascending order of age values.

We also comment on the average green shoe percentage observed in our dataset as 8%. Given that industry standards justify any amount of overallotment up to 15% of the offer size, the average displayed is realistic. Few IPOs show green shoe options exceeding 15%, however after manual confirmation on the accuracy of these values, and visual confirmation that it falls within a reasonable confidence interval of values, we conclude that they are significant in our analysis and should not be deemed outliers. The variables *gross spread* and *market return* also show reasonable distributions.

As for categorical variables, we tabulate some of our important dummies to understand the characteristics that form our dataset.

Table 6: No. of IPOs by year

Year of IPO	Freq.	Percent	Cum.
2014	239	16.16	16.16
2015	188	12.71	28.87
2016	69	4.67	33.54
2017	164	11.09	44.62
2018	168	11.36	55.98
2019	198	13.39	69.37
2020	453	30.63	100
Total	**1,479**	**100**	

Table 7: No. of IPOs and underpricing by country

Country	Obs	Mean	Std. dev.	Min	Max
Denmark	29	0.1908	0.3391	-0.2113	1.3148
Norway	82	0.1347	0.4038	-0.6571	2.8370
Sweden	127	0.0999	0.2461	-0.4511	1.2320
USA	1241	0.1564	0.3307	-0.9001	2.4938
Total	**1479**	**0.1455**	**0.3299**	**-0.5549**	**1.9694**

The year 2020, and subsequently 2021 which will be studied in a later section, are high IPO activity periods. IPO activity, which can be measured as a percentage of IPOs against all publicly listed companies in a given year, rose from 5% on average in the early years of our dataset to 13% in 2020 in the US, and up to 17% in Nordic markets. This can be construed as a rush to action as stock markets began to adjust after the pandemic. Given the increased market activity, following the market timing theory elaborated in section 3.5.2.2. Market-level factors, it can be expected that firms wished to take advantage of the liquidity present in the market, thereby increasing the number of IPOs during the period. We also see the year 2016 in our dataset having remarkably low IPO activity, which is believed to be caused by market uncertainty and firms being unwilling offer an issue in a volatile market with unclear valuations.

Table 7 shows us the number of IPOs that originate from each country in our dataset, and also details an analysis of our dependent variable *underpricing* in the context of each region. Within the observations available for Norway, we see that it has an unusually large underpricing range, but the average level of underpricing is reasonable. Although an underpricing level greater than 200% fits within our confidence interval for the entire sample, this observation may be an outlier for the region of Norway. The sporadic variability of underpricing across regions may lead to insignificance of these factors in our regression analysis.

Table 8: No. of IPOs and underpricing by TRBC industry

Industry	Obs	Mean	Std. dev.	Min	Max
Academic Services	18	0.0980	0.1787	-0.1892	0.4000
Basic Materials	35	0.1061	0.2673	-0.2193	1.1140
Consumer	149	0.1951	0.3113	-0.4108	1.4100
Energy - Non Renewables	29	0.0281	0.0796	-0.0361	0.1429
Energy - Renewables	9	0.3404	0.3600	-0.1889	1.0059
Financials	388	0.0405	0.1268	-0.6571	1.3934
Government Activity	1	0.0014	.	0.0014	0.0014
Healthcare	427	0.2104	0.4242	-0.4511	2.8370
Industrials	115	0.0928	0.2556	-0.4286	1.5995
Real Estate	52	0.0606	0.1802	-0.1338	0.8720
Technology	234	0.2625	0.3947	-0.9001	2.1700
Utilities	18	0.1740	0.3407	-0.2307	0.9844
Total	**1479**	**0.1284**	**0.2541**	**-0.3046**	**1.1069**

We see that a majority of our dataset consists of IPOs within the financials and healthcare sectors. But as expected, technology IPOs continue to be an integral part of the market with high IPOs numbers year on year. These IPOs also have higher underpricing on average, owing to a significant part of their valuations being driven by growth potential which is difficult for investors to quantify. We consider the number of renewable energy firms in our dataset as well, as it is a natural starting point for ESG analysis at an industry level. However, with only nine green energy IPOs available, sample regression estimates on the impact of this industry on underpricing may not be representative of the population.

In addition to the above, we also report that 1294 firms considered in our dataset (87.49%) price their IPOs using the bookbuilding method. However, a majority of this group consists of US IPOs, and the Nordic countries are seen to lean more toward a fixed pricing method on average. Two-thirds of the IPOs are listed on growth-forward stock exchanges such as Nasdaq, Euronext, and First North. In terms of underwriter rank, around 48% of the IPOs considered are backed by highly reputed underwriters (with a rank of 4 or 5) across regions. Finally, only 31% of the firms going public were previously backed by venture capitalists. This information gives us a better overview of the data we aim to study, without the need to consider its implications on representation in our dataset given their function as control factors.

Further analysing our data to understand the results we can expect from our regression analysis, we look a correlation matrix of our independent variables against underpricing. In order to effectively capture the effect of dummy variables as well, we calculate spearman's correlation coefficient. The dummy variables have no significant correlation with underpricing in our sample, however the dummy variables for country, specifically the *USA* country dummy is moderately correlated with a few other independent variables. We expect and justify this occurrence as distributions for variables such as pricing technique, where a majority of the IPOs under bookbuilding originate from the US, are bound to move in the same direction as the US country dummy. We nevertheless elect to retain these variables, as they are important control factors for our analysis and do not have any significant correlations with our continuous variables, eliminating the need to accommodate for biased coefficients.

We also find no significant multicollinearity between the continuous independent variables. The table below shows that most variables replicate their hypothesized relationship with underpricing as detailed in *Table 3*. However, the magnitude of correlation is lower than expected. *The ESG_dummy* variable is significant in explaining underpricing, but does not reflect the expected direction of association. This could entail that firms with ESG efforts in our model experience higher underpricing, contrary to our firm-related hypothesis, but possibly due to market sentiment-related demand for ESG that leads to higher closing prices.

Table 9: Correlation matrix

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1. Underpricing	1							
2. FirmAge	-0.021	1						
3. logFirmSize	0.1113	0.2192	1					
4. logOfferSize	0.0392	-0.1201	0.3302	1				
5. Gross Spread	0.1553	-0.0444	0.2591	-0.1728	1			
6. GreenShoePct	0.2691	-0.0084	0.1482	0.300	0.0764	1		
7. MarketReturn	0.0491	-0.0926	-0.1554	0.0479	-0.1249	-0.0222	1	
8. ESG_dummy	0.1514	0.1204	0.4832	0.2675	0.2666	0.2378	-0.1688	1

Finally, we look at our main explanatory variable i.e. Firm ESG class, and place it in the following contexts:

Table 10: Classification of IPOs into E/S/G and ESG classes

Firm Class	**E-class**	**S-class**	**G-class**	**ESG-class**
N/A	601	601	601	601
C1	12	24	33	4
C2	51	189	198	107
C3	105	450	337	426

C4	710	215	310	341
Total	**1479**	**1479**	**1479**	**1479**

Note: N/A denotes firms that do not have an ESG score and cannot be classified

First, we look at the classification of IPOs based on their individual Environmental, Social, and Governance score, and their consolidated ESG score. In the above table, despite 24 firms being classified into C1 for their social efforts, only 4 firms remain in the same class in the consolidated category. With such a situation, it is important to build our regression analysis step-by-step starting with individual E/S/G classifications, which build to a larger model with the consolidated ESG classification. In this manner, we can understand the significance and impact of firm efforts in each pillar of ESG, and analyse whether it carries over to a consolidated score.

We also look at the distribution of the *underpricing* and *offer price* values of firms grouped by ESG classes. This visual tool with help us recognise any surface-level difference in the spreads of underpricing of IPOs belonging to different classes.

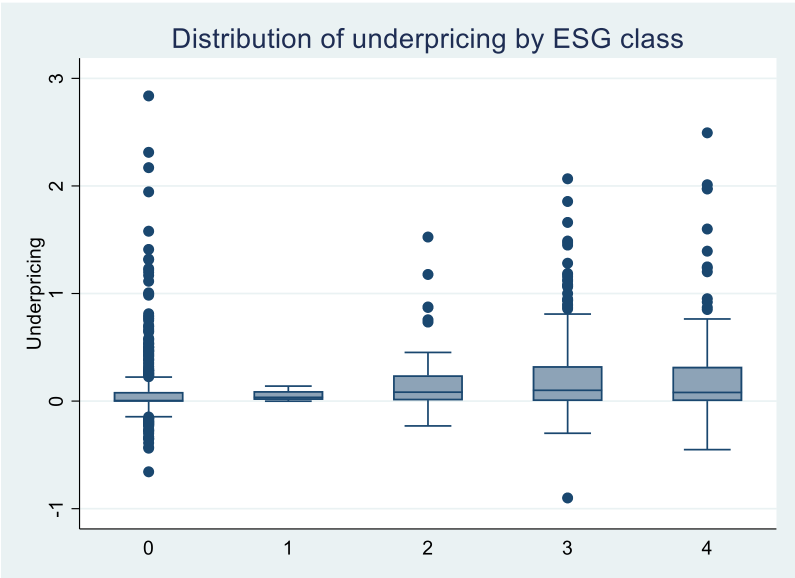

Figure 4: Box plots of underpricing by ESG class

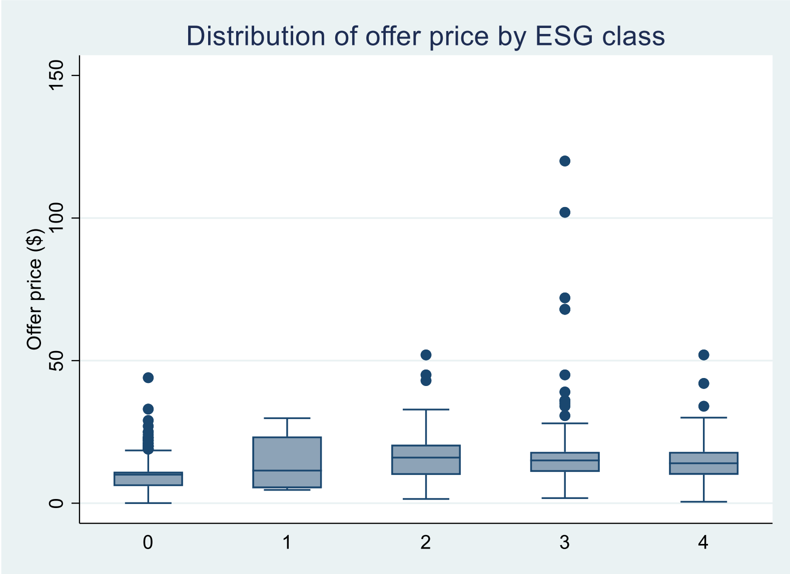

Figure 5: Box plots of offer price by ESG class

The extreme values of underpricing for each class in *Figure 4* reduce the compactness of the graph and make it difficult to view the box plot quartiles. However, we see that the average underpricing levels across ESG classes tend to cluster around similar points. Conversely, on the offer price graph, the difference between each class' mean is more obvious. Placing this comment in the context of our hypothesis, we may expect our regression to display at least a slight significance for ESG classes and their effect on pricing decisions taken by firms during their IPOs, after controlling for other effects.

5. Results and main analysis

We aim to tackle our hypotheses with a step-by-step approach that allows us to compare and judge the significance of results as we test each model. Building on a strong base regression for underpricing gives validity to the robustness of our results and helps us understand the marginal effect of adding ESG and other variables to our analysis.

5.1. Base underpricing model

We begin by defining our regression model for underpricing with the independent variables identified in previous sections. We have

$$
\begin{aligned}
Y_{underpricing\_i} = {} & \alpha + \beta_1 \text{ Firm age}_i + \beta_2 \ln(\text{Firm size})_i + \beta_3 \ln(\text{Offer size})_i + \\
& + \beta_4 \text{ Market return}_i + \beta_5 \text{ Gross spread}_i + \beta_6 \text{ Greens shoe}_i + \\
& + \beta_7 \text{VC dummy}_i + \beta_8 \text{Pricing technique}_i + \beta_j \text{Country}_{ji} + \beta_k \text{Industry}_{ki} + \\
& + \beta_y \text{Year}_{yi} + \beta_s \text{Stock exchange}_{si} + \beta_r \text{Underwriter rank}_{ri} + \varepsilon_i \qquad (7)
\end{aligned}
$$

To estimate this model, we use the Ordinary Least Squares (OLS) method. This model allows us to estimate unbiased coefficients that accurately capture the effect of each control variable on underpricing, given model assumptions are met. We have shown the absence of multicollinearity in section *4.1.2 Descriptive statistics*. Other assumptions include homoskedasticity, normality of residuals, and independence. We will use post-estimation tests to check for any violations to these assumptions.

We also find OLS widely used in underpricing literature to estimate complicated models for IPO decision making (Loughran and Ritter, 2002; Gonzalez et al., 2019). Other methods such as Hireachical Linear Modeling (HLM) are used to model data that cluster at levels such as firm, industry, or country. However, HLM helps in estimating the differences in models across clusters when the aim of the study is to understand the independent impact of such clusters on results, where OLS regressions may not give accurate estimates (Baker et al., 2021). However, despite having a cluster at the country / region level, the purpose of our study warrants the use of country dummies solely as control variables, with OLS as a viable estimator (Boulton, 2010).

Results of our OLS base regression are reported in *Table 12* under model (1). We find that our model specification in Eq (7) does a fair estimation of underpricing within our dataset. Underpricing and other values expressed in percentages show as point units in our results i.e. 0.15 instead of 15% as an integer). The power of our OLS model, measured by its R^2 (0.197) and adjusted R^2 (0.176), is fair and compares well to other models estimated in past literature. From our main control variables, we find *green shoe percentage, year 2020 dummy, VC dummy, bookbuilding dummy, and Norway* and *Sweden dummies* to be significant and displaying the relationship hypothesized in section *4.1. Preliminary analysis*. Ln firm size is also significant at a 90% confidence interval, but shows that a 1% increase in firm size (total assets) leads to a positive 0.000048 percentage point increase in underpricing. This is not in line with our hypothesis where larger firms tend to experience lower underpricing. This is also observed in the case of ln offer size, and hence may be attributed to the localised characteristics of our dataset.

The year dummy for 2020 is highly significant, and shows a positive relation with underpricing, increasing the latter by 0.110 percentage points over 2014 (reference group), with everything else constant. This follows the hot-issue market effect for 2020 as discussed earlier, explaining higher underpricing for an IPO issued in the year. Other years do not have a significant marginal effect on underpricing.

We see that a higher green shoe percentage is associated with higher underpricing, in line with our underwriter incentive theory. A significant bookbuilding dummy also shows that bookbuilt IPOs face lower underpricing than fixed deals as expected. Other variables such as *firm age* (-ve), *gross spread* (+ve) , and *market return* (+ve) are insignificant in our analysis, but display a directional relationship with underpricing as hypothesized earlier.

Looking at our dummy variables for country, we find *Norway* and *Sweden* to have significantly lower underpricing compared to *Denmark*. We hope to investigate this phenomenon in our extended ESG analysis where we consider country-level ESG scores and regulations. Coefficients for other dummy variables including *industry*, *stock exchange*, and *underwriter rank* have not been displayed in the results table due to space limitations, but are significant in our analysis.

We find the *Tech* industry dummy to be significant ($p<0.05$) with a positive coefficient of 0.107, as expected given the relative difficulty in valuing such growth-oriented companies. We also find the *Renewable energy* dummy to be significant ($p<0.05$), and display a positive relation with underpricing. Although this is contrary to our hypothesis for the industry, we note that our sample only consists of nine IPOs within the sector, severely compromising its representation. *Government activity* (+ve) and *Consumer* (-ve) industry are also found significant at a 90% confidence level.

We conclude that underwriter rank dummies are jointly significant in our analysis, but do not display a strong linear pattern on the progressive impact of each rank on underpricing. From our results, more prestigious underwriters are associated with lower underpricing which is contrary to our expectations. We also find the stock exchange dummies to be neither individually nor jointly significant in our results.

Overall, our hypothesized model in Eq(7) explains underpricing in our dataset to a reasonably fair level, and gives us concrete associations between our dependent and base explanatory variables. The addition of interaction terms between country and year / industry / gross spread (results not displayed here), does not increase the power of our model and may lead to overfitting. We therefore consider the unchanged base model highlighted in *Table 12* *model (1)* to be a suitable starting point for our detailed ESG analysis.

Before proceeding, we run some quick tests on the residuals and estimates of the above model to check for violations to OLS assumptions which may bias results. With a joint test for skewness and kurtosis, and a visualization of the distribution of errors, we find the normality assumption to hold ($p<0.05$). Plots of the residuals against fitted values and explanatory variables show that the independence assumption is satisfied as well. While running the original model, a command for robust i.e. white standard errors was included to correct for potential heteroskedasticity. Hence post-estimation tests for the assumptions return negative. With no violations encountered, we conclude that the OLS method is robust in our analysis.

5.2. Selection bias estimation

In building our base regression model to include ESG variables, we find that our proposed methodology in Eq (3) may embed a selection bias. As our hypothesis under *section* *3.3. Hypothesis 2: classes of ESG firms* entails the analysis of a subset of our data, specifically firms that can be segregated into ESG classes, we subject our results to bias by only considering observations that fit a given criteria. A detailed introduction to the problem and established methods to overcome the bias is shown in *section 3.4*.

As a preliminary test, we look at the distribution of firms in our dataset based on the *ESG_dummy* variable of having a ESG score. From *Table 10*, we see that 878 firms out of our sample of 1479 have an ESG score and can subsequently be segregated into ESG classes. Hence, this subset forms 59% of our original data. This may be construed as slight bias with non-random sampling if we are to split our data and run our ESG regression on the 878 firms alone.

We now test for and correct any potential selection bias in our data through an endogenous variable-treatment regression, where a selection model for *ESG_dummy* is nested within the main underpricing regression as formulated in Eq (4) and Eq (5).

Table 11: Endogenous treatment-variable regression results

Underpricing	**Main model (1)**
Firm age	-0.0004
	(0.0006)
Ln firm size	0.0081
	(0.0051)
Ln offer size	0.0084
	(0.0104)
Gross spread	0.9780
	(0.743)
Green shoe pct	1.288***
	(0.117)
Market return	0.0243
	(0.117)
Y2020_dummy	0.111***
	(0.0278)
Y2019_dummy	0.0213
	(0.0296)
Y2018_dummy	0.0254
	(0.0308)
Y2017_dummy	0.0221
	(0.0313)
Y2016_dummy	0.0326
	(0.0416)
Y2015_dummy	0.0227
	(0.0291)
PT_bookbuilding	-0.077*
	(0.0446)
VC_dummy	0.113***
	(0.023)
ESG_C1_dummy	0.0676
	(0.156)
ESG_C2_dummy	-0.0129
	(0.0383)
ESG_C3_dummy	0.0005
	(0.0226)
ESG_dummy	-0.0338
	(0.0604)
Constant	-0.1650
	(0.112)
ESG_dummy	**Selection model (2)**
Ln firm size	0.201***
	(0.0164)
Firm age	0.00201
	(0.0037)
CSRreport_dummy	2.858***
	(0.39)
USA_dummy	1.510***
	(0.444)
Norway_dummy	-0.185
	(0.495)
Sweden_dummy	1.388***
	(0.462)
Constant	-1.756***
	(0.507)
Observations	1479
rho	0.146

*Note: Industry, exchange, underwriter rank dummy used in Main (1). Industry used in Selection (2). Standard errors reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

With the estimated results in *Table 11*, we look at the statistic rho (ρ) that captures the correlation between the error terms of the selection model and the main underpricing model. A strong correlation indicates that both models are estimated by identical processes, thereby showing grounds for potential selection bias. We see that the value of ρ in our model is 0.146, indicating low correlation and subsequently low selection bias in our methodology. This suggests that data for firms without ESG is missing randomly from our sample, referring to the 59% v. 41% distribution above and rendering it admissible within a fair confidence interval.

We also find that the regression estimates calculated by this method are comparable to OLS regression results under certain circumstances (Cuddeback et al., 2004). Given that model assumptions for both our methodologies are reasonably satisfied, we look at the differences between significant coefficients in the main underpricing models across *Table 11 model (1)* and *Table 12 model (1)*. We note that the selection model estimates include ESG control factors, whereas our base underpricing model does not. But as these variables are insignificant in *Table 11 model (1)* and do not correlate with factors we wish to study, we expect the coefficients of the significant underpricing control variables to be unaffected by this inclusion.

The estimates for variables such as *firm age*, *ln firm size*, *green shoe percentage*, year *2020* dummy, *bookbuilding*, and *VC dummy* show little to no significant change against the estimates in *Table 12 model (1)* i.e. our base underpricing model. This further confirms that modeling a selection equation does not improve the estimation of regression results in our analysis in the absence of selection bias.

With this understanding, we elect to proceed with our ESG analysis as per the hypothesis set out in *section 3.3*. using OLS estimation.

5.3. ESG analysis

5.3.1. Regression with ESG dummy

With a fair underpricing estimation model, we begin to test the main hypotheses set out at the beginning of this paper. Under section *3.1. Hypothesis 1: ESG alignment*, we argue that a firm actively taking ESG efforts is likely to experience lower underpricing on its IPO than other firms which do not take such efforts. We proxy the factor of “taking ESG efforts” with our *ESG_dummy* variable that captures if a firm has an ESG score.

Building on our base regression, we add the ESG_dummy variable and estimate our model using OLS, with a command for robust standard errors. *Table 12 model (2)* shows the added coefficient for *ESG_dummy* as significant at a 5% level, with a value of 0.0336. This entails that a firm having an ESG score (i.e. taking ESG efforts) has 0.0336 percentage points higher underpricing than firms who do not have a score. This means that we reject our first hypothesis that ESG efforts reduce IPO underpricing. We also notice that the correlation found in *Table 9* between *ln firm size* and *ESG_dummy* has an effect on our model, where significance is awarded to the *ESG_dummy* variable but removed from *ln firm size*. However, given that each of these factors is important as a control / main variable respectively, we choose to retain both in our regression but agree to be mindful of its implications on variable significance.

Previous research that studies the relationship between firm level ESG alignment and IPO performance in general finds negative correlations between the two factors, similar to our hypothesis (Fenili and Raimondo, 2021; Reber et al., 2021). However, our result contradicts intuition and past literature and must be studied further.

Alternative theories that look at the impact of ESG alignment on first-day returns from a market sentiment point of view, argue that after controlling for firm-level factors, a firm with ESG efforts is likely to experience greater demand on its IPO, thereby increasing the return observed on its first day of trading (Da et al., 2011). We recognise the similarity of our control variables with the model introduced in such papers, and find that it may be reasonable to observe a positive relation between ESG efforts and returns in our analysis. This however entails a redefinition of our dependent variable and firm-related hypothesis, which deems this conclusion out of the scope of this paper.

Looking at the distribution of underpricing across ESG classes in *Figure 4*, we see that the average level of underpricing for firms that have an ESG score (regardless of class segregation) is significantly higher than that of firms without ESG scores. We also note that 59% of our sample has an ESG score. With such a weight, the average underpricing between 878 firms (59%) is bound to be significantly different then the averages of its sublevels i.e. ESG classes. Hence, fitting a regression model with a condensed binary variable of ESG efforts may impact the ability of the model to estimate a coefficient that reflects the entire sample and its categories. This is a natural point of transition to our second hypothesis that looks at individual ESG classes and their impact on underpricing.

In addition, we see that the study of such a relation in the context of IPOs is better done with matching samples that equally represent both categories of the binary variable. In Reber et al. (2021), ESG disclosure is a dummy variable that captures if a firm discloses it ESG efforts similar to our *ESG_dummy*. Given the nature of this variable, the authors develop a balanced sample with each ESG-IPO having a closely comparable non-ESG counterpart, avoiding any bias or skewness in results. We recognise the shortfalls of our method in comparison to the above given the specifications of the hypothesis we wish to test, but recognise the difficulty in implementing such alternatives at the cost of sample size and room for model development.

We conclude on our first hypothesis that firms having an ESG score experience higher IPO underpricing than firms without a score in our sample, contradicting our expectations. However, the introduction of this variable marginally improves the predictive power of our underpricing model, thereby validating (albeit weakly) our claim that ESG efforts augment models in existing literature, and can capture previously unexplained factors in first-day returns. This acts as an interesting foundation for future ESG research on the relevance of efforts on a firm's decision to adjust its valuation in order to have access to capital. Subtopics include understanding the relevance of ESG efforts in a firms' preference for financing type / capital structure, and an extended application of ESG as an explanatory variable for IPO performance.

Under the assumption that ESG efforts reduce information asymmetry, the standalone implication of this statement is that ESG efforts may not be fully recognised and priced in IPO markets, as firms potentially continue to underprice their shares expecting market efficiency on ESG information to be weak, thereby having to incentivise investors.

5.3.2. Regression with ESG class

Tackling our second and main hypothesis that aims to study the extent to which underpricing differs between classes of ESG firms, we consider our base regression model, the ESG_dummy, and our ESG class dummies for our analysis.

A firm that has an ESG score can be placed into one of four ESG classes ranging from Class 1 to Class 4, with Class 1 indicating the highest level of ESG. This leads us to make three class dummies where we consider C4 to be our reference group.

We also recognise that these ESG class dummies are nested in the *ESG_dummy* variable as they only originate if the value of *ESG_dummy* is equal to one. To accommodate for this relationship, we create interaction terms for each ESG class dummy with the *ESG_dummy* variable and include them in our analysis instead of the standalone class dummies. To control for the representation of firms that do not have an ESG score (*ESG_dummy* = 0), we include the *ESG_dummy* variable as a main effect. The results of this regression is displayed under *model (3)* in Table 12 seen below.

Table 12: Regression results

Underpricing	**Base (1)**	**Score_avail (2)**	**ESG Level (3)**
Firm Age	-0.0004 (0.0004)	-0.0004 (0.0004)	-0.0004 (0.0004)
Ln firm size	0.0048* (0.0026)	0.0034 (0.0027)	0.0036 (0.0028)
Ln offer size	0.0114 (0.0111)	0.0081 (0.0112)	0.0086 (0.0113)
Gross spread	1.1760 (0.737)	1.0190 (0.73)	0.9550 (0.738)
Greenshoe pct	1.302*** (0.114)	1.280*** (0.115)	1.287*** (0.115)
Market return	0.0290 (0.103)	0.0326 (0.103)	0.0293 (0.103)
Y2020_dummy	0.110*** (0.0295)	0.111*** (0.0296)	0.110*** (0.0294)
Y2019_dummy	0.0253 (0.0276)	0.0213 (0.0277)	0.0208 (0.0278)
Y2018_dummy	0.0316 (0.025)	0.0256 (0.0253)	0.0248 (0.0253)
Y2017_dummy	0.0277 (0.0252)	0.0222 (0.0257)	0.0224 (0.0257)
Y2016_dummy	0.0385 (0.05)	0.0296 (0.0507)	0.0313 (0.0508)
Y2015_dummy	0.0233 (0.0286)	0.0215 (0.0286)	0.0221 (0.0287)
USA_dummy	-0.1400 (0.106)	-0.1370 (0.106)	-0.1360 (0.106)
Norway_dummy	-0.225** (0.1)	-0.222** (0.1)	-0.219** (0.1)
Sweden_dummy	-0.181* (0.0957)	-0.187* (0.0959)	-0.185* (0.0962)

PT_bookbuilding	-0.0724*	-0.0698*	-0.0726*
	(0.0391)	(0.0391)	(0.0397)
VC_dummy	0.115***	0.112***	0.112***
	(0.0249)	(0.0247)	(0.0249)
ESG_dummy		0.0336*	0.0371*
		(0.0187)	(0.0221)
ESG_C1_Avail			0.0529
			(0.081)
ESG_C2_Avail			-0.0276
			(0.0319)
ESG_C3_Avail			-0.0045
			(0.0234)
Constant	0.0264	0.0372	0.0389
	(0.108)	(0.108)	(0.108)
Industry dummy	Yes	Yes	Yes
SE dummy	Yes	Yes	Yes
Underwriter rank dummy	Yes	Yes	Yes
Observations	1479	1479	1479
R-squared	0.197	0.202	0.199
Adjusted R-squared	0.176	0.179	0.175

*Note: Standard errors reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

In our model, we see that the variables *underwriter rank*, *VC dummy*, and *green shoe percentage* continue to be the most significant explanatory factors for underpricing. This may entail that the model holds little space for ESG to have a pronounced role in predicting an average level of underpricing.

We see that the *ESG_dummy* variable is still significant ($p<0.10$). Looking at our class interaction dummies, we unfortunately find that none of them are significant in explaining underpricing. However, given that an ESG score is available, we see that a firm of ESG class 3 has 0.0045 percentage points lower underpricing than a class 4 firm. A firm of ESG class 2 has even lower underpricing in comparison. The coefficient for ESG class 1 however shows that firms that fall into this category experience higher underpricing that a class 4 firm, contradicting our expectations. But we note that only four observations in our sample belong to ESG class 1, thereby affecting representation in the model. Overall, we see that our hypothesis holds, but is not significant in our dataset or model. A joint significance test for the ESG class interaction terms fails to reject the null hypothesis, showing no marked difference in the coefficients of these classes.

The implication of this result is that ESG class does not play a significant role in firm decision-making in the context of IPOs, where underpricing does not differ between classes of ESG firms. For firms, this could mean that their ESG efforts are not efficiently priced in the market, making it difficult to obtain a fair valuation that reflects their internal estimates, and thereby forcing them to lower their offer price.

An extension of the market efficiency-linked theory above is the understanding of investor resources that limit the market's ability to assimilate ESG class information. A potential investor conducting research on an IPO of interest may undertake manual analysis by looking at the operations, industry, or long-term vision to judge the ESG alignment of a firm. In this case, an investor may only have a surface-level understanding of the ESG efforts of a firm. Investigating further details on such alignment may be time-consuming and simply not of interest to the average investor. Although institutional or ESG-aware investors may seek out such information and price their valuations accordingly, the overall market will still be inefficient in recognising the differences in ESG classes of firms. Including ESG class as an explanatory variable for underpricing in current markets thus leads to insignificance, but shows the expected impact on underpricing as hypothesized. This will allow for future research to build on our model, possibly with focus on particular regional markets, time frames, or industries.

On the other hand, we also look at insignificance as a result of weaker firm communication. Our hypothesis that firms are aware of their ESG levels and price their offers for an efficient market depends on the assumption that firms believe they have communicated sufficient information to investors to recognise such levels in alignment. During an IPO, a firm may adjust its pricing to be reflective of its ESG efforts and the subsequent value addition stemming from such efforts. However, if such efforts are not disclosed in detail to investors, the information asymmetry problem continues and firms cannot achieve a matching valuation.

As the availability of ESG information, awareness of ESG investing, and mandates on disclosure increase in the coming years, we hypothesize our methodology and analysis to have significant applicability in underpricing theory.

5.3.3. Regression with E/S/G classes

With the results above, it may be of interest to test whether these effects are observed for individual pillar scores of E/S/G as well. *Table 13* displays a comparison of regression coefficients across five models including a general ESG efforts model with *ESG_dummy* alone, separate regressions for each ESG pillar, and a consolidated regression for overall ESG class.

Table 13: ESG regression results

Underpricing	**Score_avail**	**E Level**	**S Level**	**G Level**	**ESG Level**
Firm age	-0.0004	-0.0004	-0.0004	-0.0005	-0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Ln firm size	0.0034	0.0034	0.0031	0.0032	0.0036
	(0.0027)	(0.0027)	(0.0028)	(0.0027)	(0.0028)
Ln offer size	0.0081	0.0094	0.0081	0.0085	0.0086
	(0.0112)	(0.0114)	(0.0113)	(0.0112)	(0.0113)
Gross spread	1.0190	0.9250	1.0360	1.0230	0.9550
	(0.73)	(0.735)	(0.736)	(0.732)	(0.738)
Green shoe pct	1.280***	1.281***	1.279***	1.275***	1.287***
	(0.115)	(0.115)	(0.115)	(0.116)	(0.115)
Market return	0.0326	0.0288	0.0315	0.0338	0.0293
	(0.103)	(0.103)	(0.103)	(0.103)	(0.103)
Y2020_dummy	0.111***	0.109***	0.112***	0.111***	0.110***
	(0.0296)	(0.0297)	(0.0295)	(0.0296)	(0.0294)
Y2019_dummy	0.0213	0.0189	0.0213	0.0210	0.0208
	(0.0277)	(0.0279)	(0.0277)	(0.0277)	(0.0278)
Y2018_dummy	0.0256	0.0237	0.0260	0.0242	0.0248
	(0.0253)	(0.0253)	(0.0254)	(0.0255)	(0.0253)
Y2017_dummy	0.0222	0.0220	0.0225	0.0213	0.0224
	(0.0257)	(0.0257)	(0.0258)	(0.0257)	(0.0257)
Y2016_dummy	0.0296	0.0336	0.0291	0.0280	0.0313
	(0.0507)	(0.0513)	(0.051)	(0.0511)	(0.0508)
Y2015_dummy	0.0215	0.0214	0.0210	0.0198	0.0221
	(0.0286)	(0.0288)	(0.0287)	(0.0287)	(0.0287)
USA_dummy	-0.1370	-0.1360	-0.1360	-0.1410	-0.1360
	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)
Norway_dummy	-0.222**	-0.215**	-0.222**	-0.223**	-0.219**
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Sweden_dummy	-0.187*	-0.18*	-0.187*	-0.186*	-0.185*
	(0.0959)	(0.0965)	(0.0962)	(0.0965)	(0.0962)
PT_bookbuilding	-0.0698*	-0.072*	-0.0703*	-0.0677*	-0.0726*
	(0.0391)	(0.0393)	(0.0396)	(0.0395)	(0.0397)
VC_dummy	0.112***	0.111***	0.111***	0.112***	0.112***
	(0.0247)	(0.0247)	(0.025)	(0.0248)	(0.0249)
ESG_dummy	0.0336*	0.0409**	0.0259	0.0341	0.0371*
	(0.0187)	(0.019)	(0.0241)	(0.0227)	(0.0221)
E_C1_Avail		-0.0693			
		(0.0623)			
E_C2_Avail		-0.0120			
		(0.0404)			
E_C3_Avail		-0.0635**			
		(0.0302)			
S_C1_Avail			0.0190		
			(0.058)		
S_C2_Avail			0.0069		
			(0.0323)		
S_C3_Avail			0.0136		
			(0.0263)		
G_C1_Avail				-0.0344	
				(0.0331)	
G_C2_Avail				0.0174	
				(0.0298)	
G_C3_Avail				-0.0064	
				(0.0246)	
ESG_C1_Avail					0.0529
					(0.081)
ESG_C2_Avail					-0.0276
					(0.0319)
ESG_C3_Avail					-0.0045
					(0.0234)
Constant	0.0372	0.0371	0.0362	0.0376	0.0389
	(0.108)	(0.108)	(0.108)	(0.108)	(0.108)
Industry dummy	Yes	Yes	Yes	Yes	Yes
SE dummy	Yes	Yes	Yes	Yes	Yes
Underwriter rank dummy	Yes	Yes	Yes	Yes	Yes

Observations	1479	1479	1479	1479	1479
R-squared	0.202	0.201	0.199	0.199	0.199
Adjusted R-squared	0.179	0.177	0.175	0.176	0.175

*Note: Standard errors reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Results show that the predictive powers (adjusted R^2) of individual S/G pillar regressions are not significantly different than the consolidated ESG class model. However, a model that includes Environmental classification of firms alone shows an improved fit, along with a significant E class variable. The coefficient for *Eclass 3* is statistically significant at a 5% level and shows that a firm belonging to the class experiences lower underpricing that a class 4 firm, given other variables remain constant. This result supports that the direction of our general hypothesis is valid, but the environmental factor on its own tends to be better priced in current financial markets than a consolidated score. Given that climate change and other important conversations around sustainability center on the environment pillar of ESG, we can expect investors to be more aware and vocal in this aspect, allowing high E class firms to receive a fair valuation on their IPOs. Insignificant results for other E classes and the entire G regression also show that the segregation of a firm into any one of these levels on average reduces the level of underpricing it can expect on its IPO, with all else constant. However, the regression with S classes shows a conversely positive yet still insignificant association with underpricing for all levels. Overall, none of the E/S/G class dummies are jointly significant in explaining underpricing in their respective models.

Across *Table 13*, we also look at the country dummy variables to understand the impact of ESG between regions. The introduction of interaction effects between the country and ESG class dummies is seen to be insignificant, and hence omitted from the regression analysis. The main country effect dummies capture enough information for us to build our conclusions. Similar to our base underpricing model in *Table 12 model (1)*, coefficients for the Norway and Sweden dummies are significant at 5% and 10% levels respectively. We see that an IPO originating from Norway experiences lower underpricing on average compared to our reference country Denmark, with other variables constant. This is in line with our research on the relatively higher country-level ESG efforts in Norway and relevant theory on the applicability of such efforts on firm-level underpricing (Boulton et al., 2010; Engelen and van Essen, 2010).

Refinitiv country ESG scores rate Norway at a 9.25 on a 10-point scale, with Sweden and Denmark scoring 9, and USA scoring 8 (Refinitiv, 2020). These scores are a consolidation of several quantifiable metrics that measure a country's progress towards UN Sustainable Development Goals (SDG). The ESG effort in Norway is thus supported by the recent developments in ESG regulations and the overall country score as per Refinitiv. Sweden also shows a negative association with underpricing, further proving results of past country-level research in ESG and IPOs, and the added effect of EU taxonomy. Finally, comparing our regional samples i.e. USA and Nordics, a joint significance test shows us that there is a statistically significant difference between the underpricing levels across these regions.

After confirming the non-existence of selection bias, we may also choose to run these models on a subsample of our dataset that only includes firms with ESG scores (without the need for *ESG_dummy* and subsequent nested variables). With 878 observations, such an analysis leads us to similar conclusions as above, where ESG or E/S/G class does not have a significant impact on underpricing. This proves the robustness of our nested variable approach, and its benefits in allowing us to work with a larger sample size.

5.4. Out-of-sample analysis

Our analysis so far has been limited to our proposed in-sample dataset spanning the year 2014-2020. With our results, it may be of interest to test the predictive power of our regressions on an out-sample that is expected to have similar characteristics to our estimation sample. A good model should be able to predict values of underpricing for the new sample with reasonable accuracy, given no unexpected changes in variable relationships are observed. We begin by looking at some summary statistics that give us an overview of the out-sample we wish to use.

Table 14: Descriptive statistics - 2021

Variable	**Obs**	**Mean**	**Std. dev.**	**Min**	**Max**
Underpricing	519	0.1839	0.4454	-0.5652	4.05
Firm age	519	6.0385	11.1987	0	116
Ln firm size	519	1.8118	3.4112	-6.1193	10.0901
Ln offer size	519	4.9933	1.2891	-0.5836	8.4229
Gross spread	519	0.0424	0.0215	0.0007	0.1243
Green shoe	519	0.0674	0.0745	0	0.3073
Market return	519	0.0678	0.0192	-0.035	0.136

Table 15: No. of IPOs by country and ESG class

	ESG class			
Country	**0**	**3**	**4**	**Total**
Denmark	11	1	0	12
Norway	47	0	0	47
Sweden	23	1	1	25
USA	419	5	11	435
Total	**500**	**7**	**12**	**519**

Our new sample consists of IPOs across the US and Nordics that have occurred before the end of June 2021. We have 519 IPOs to consider, and data on all our explanatory factors are available for these observations.

If we assume that markets for IPOs in 2021 have greater awareness of ESG efforts and a marked efficiency is pricing potential differences in ESG classes for IPO firms, then our proposed model will predict underpricing data better for 2021, than for our in-sample data. However, *Table 15* shows that only 19 IPOs out of the total sample have an ESG score, within which representation is only seen for class 3 and class 4 firms. This may have a considerable impact on the suitability of our base model and the resulting estimates. Nevertheless, the existence of underpricing control factors in our models should give us some fair estimates to work with.

For our predictions, we consider the model explained in *section 5.3.2.* and *Table 12 model (3)* that estimates underpricing with ESG class dummies and a nested variable approach. The predictive power of this model, measured by its R^2 is 17.5%, which is fair compared to past research in the field. However, in considering this model as a base for out-of-sample predictions, the goodness-of-fit of the model may not be sufficient to capture the effects inherent in the out-sample and accurately predict underpricing values. Though we have models with greater predictive power, we choose to proceed with our analysis using the above as it includes variables that are important to our main hypothesis.

For the new dataset, we predict values of underpricing with our regression coefficients from *Table 12 model (3)*. To test the accuracy of predictions, we calculate a correlation coefficient between the predicted values and the actuals. Squaring the coefficient, we get an R^2 of 7.66%. This is arguably a low statistic, and shows that our model does not translate well to other samples. Although out-of-sample predictions have lower model-fit statistics, this unusually lower value indicates that there are trends and unobserved associations in the 2021 data that we cannot capture in the model that we have defined for IPOs before 2021.

This result weakly shows that markets in 2021 do not recognise or adjust values for different classes of ESG firms within our dataset. However, samples with more balanced representation of firms may fair better using our proposed model, thereby providing ground for future research.

5.5. Post-IPO performance

To further develop our understanding on the impact of ESG efforts on IPOs, we briefly consider an analysis of the post-IPO performance of firms and compare these results across ESG classes. We begin with a dataset of our ESG-scored firms, with 878 observations and collect information on their price performance across a 6 month-period following their IPO. After removing firms that do not have comprehensive price data available for the period considered, we finalise our dataset with 789 observations.

To understand the post-IPO performance of these firms, we consider the 3-month and 6-month returns on their respective IPO offer prices. These returns are subsequently market adjusted with the average 3-month and 6-month returns of major stock indices in the country of listing, measured from the date of IPO. This allows us to examine the independent price trend of each IPO after accounting for market wide fluctuations.

Table 16: Descriptive statistics for post-IPO performance measures

Variable	Obs	Mean	Std.dev.	Min	Max
M3MAreturn	789	0.3271	0.6946	-0.9501	5.2257
M6MAreturn	789	0.2769	0.7449	-1.0957	4.7473

Previous research shows that IPOs with marked ESG disclosure and efforts have lower stock volatility and subsequently higher returns in post-IPO trading than regular firms (Reber et al., 2021; Huang et al., 2019). We hypothesize similarly that the 3-month and 6-month market-adjusted returns on high ESG class firms will be larger on average than low ESG class firms in our dataset. We also consider statistical tests to prove the significance of our result by testing the differences in means across groups.

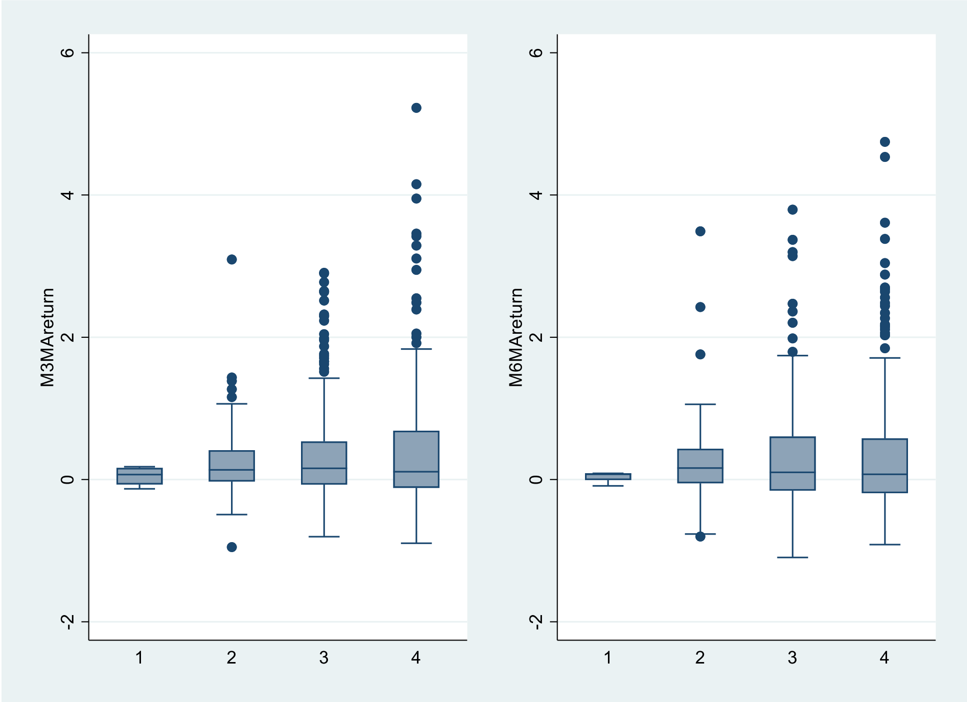

Figure 6: 3-month and 6-month market-adjusted returns by ESG class

Figure 6 shows us that there is a slight difference between the mean return levels across ESG classes for both market-adjusted return measures. With the exception of ESG class 1, mean returns are on average higher for high ESG firms (class 2 and class 3) compared to low ESG firms in class 4. This arbitrarily validates our hypothesis in line with past literature. We however test for the significance of such observed differences using group mean comparison methods such as ANOVA.

For ANOVA, we consider the assumptions that groups must meet in order to generate valid results. We first recognise our continuous variables as the 3-month and 6-month market adjusted returns, with our grouping variable as ESG class. These series follow normal distributions and values within ESG groups are independent. However, the sample size for each group is uneven in our dataset, where we have only four observations for class 1, compared to 381 observations for class 4. This issue leads us to an alternative non-parametric method of group comparison known as the Kruskal-Wallis test.

The Kruskal-Wallis equality of populations rank test returns insignificant for both 3-month and 6-month market-adjusted returns, with p-values much higher than acceptable significance levels. This indicates that there is no significant difference in the mean returns of each ESG class for either measure. The result may entail that the impact of ESG efforts possibly stabilizes after an IPO, thereby resulting is no marked variation between ESG classes. This is an interesting proposition that opens the possibility and requirement for further analysis on such a phenomenon under different circumstances. Recommendations for studies to build on this test of ESG and IPO association are to include non-ESG firms in the analysis, and to adopt a matching concept that will allow for a more accurate comparison of the differences between ESG and non-ESG firm performance.

6. Conclusion

This paper aims to shed light on the pricing of ESG efforts taken by firms and the notion that these initiatives bridge the gap between valuations placed on the firm by potential investors and internal stakeholders. In the context of a new issue, a company is primarily challenged in the way it decides to disclose information regarding the viability of its operations to unaware investors. When firms have higher ESG disclosures and greater transparency, investors have access to more information to supplement their decision-making. Considering the proven impact of ESG on financial performance and sustainability, we hypothesize that investors place greater value on firms that undertake relatively large ESG measures, and those that actively disclose their policies.

In particular, the topic of ESG and IPOs has been of great interest to researchers who wish to study the materiality of firm efforts and how they are priced in the market. Previous studies establish a connection between IPO underpricing and ESG efforts using proxies for the latter when firm-level measures are not widely available. These proxies include country-level ESG regulations, legal and governance frameworks, and country-specific ESG scores. On a smaller scale, some studies adopt textual analysis of company filings to determine ESG alignment. However, this method has its limitations with reference to model specifications and subjectivity bias. The scattered presence of such research with reliable firm-level factors motivates us to propose and pursue a quantitative model that effectively captures firm ESG effort in the analysis of IPO underpricing.

We argue that firms which undertake higher ESG efforts, and thus belong to a higher class of ESG firms, experience lower underpricing on their first day of trading than firms who take significantly less or no such efforts. This is largely attributed to reduced information asymmetry between market participants, a factor that otherwise traditionally characterises an IPO. The added dimension of class-level analysis of ESG’s impact on underpricing, helps us understand the depth of

ESG materiality better. We identify Refinitiv's ESG scores as transparent and robust base measures for our classification, allowing us to effectively quantify firm-level factors.

We first build a base underpricing model that includes well-established control factors for our analysis. With a suitable base, we test for a binary ESG efforts variable and find that ESG efforts significantly increase the level the underpricing observed for an IPO. This contradicts past literature on the topic which report that ESG has a significantly negative impact on IPO underpricing. We distinguish the methodology used in this paper with prior research and learn that testing for such a binary variable requires a balanced dataset for robust results. We also hypothesize the unexpectedness of this association to be a result of improper consolidation of firm characteristics, where a simple binary variable may not capture on average the true effect of ESG on underpricing across its subsets.

We then proceed with a detailed ESG analysis that overcomes the above-mentioned limitation and allows us to test our primary hypothesis. A caution point in the definition of our hypothesis is that we restrict ourselves to understand the difference between ESG classes, a segregation that can only occur if a firm has an ESG score assigned. To test whether such a restriction may cause sample selection bias, we employ an endogenous variable-treatment regression method which is an extension of the widely used Heckman selection model. In estimating this method with a base and control function simultaneously, we find that selection bias is our analysis is negligible and need not be modelled for our ESG analysis.

With OLS methods, we first estimate an extended ESG model with a nested variable approach. This model includes ESG score availability as a dummy variable main effect, and the interaction terms between score availability and ESG class dummies along with underpricing control factors from our base model. The nested variable approach ensures representation of firms that do not have an ESG score, and allows us to test our hypothesis on a larger sample without bias.

We find in our results that the ESG class dummies are jointly insignificant, showing that the average level of underpricing observed does not differ between classes of ESG firms. The individual dummies are also insignificant but show that a firm of ESG class 3 or class 2 experiences lower underpricing than a firm of ESG class 4. This supports the direction indicated in our hypothesis, but does not significantly prove it. Regressions on the impact of classes of each E/S/G pillar show that environmental classification has a significant impact on underpricing, but this effect does not carry when studied under a consolidated ESG classification.

In conclusion, we find that our research question tackles a specific and pertinent issue in the topic of ESG and IPO performance with regard to firm-level factor quantifications and the application of such measures in traditional underpricing models. Although our results do not show a significant association between ESG score-based classifications and IPO underpricing, our multi-layer ESG analysis model provides literature with a flexible base upon which studies can build more robust tests for the proposed relation. In reviewing our results from both in- and out- sample estimations that cover a wide range of years, we propose that financial markets do not currently recognise and value the differences in ESG effort levels of firms. But we pave the path for future research to test the validity of this statement under market conditions in the coming years.

As recommendations for future research, we advise short-term studies to focus on strengthening the proof behind ESG's association with IPO performance under different conditions, before considering a deep dive into the impact of subtopics of ESG on such metrics. Given that conversations around ESG are a relatively new phenomenon in financial markets, studies that aim to test subtopics immediately may not find relevance in minor technicalities when the general consensus surrounding ESG as a whole is still uncertain. For studies that wish to continue our work on the subtopic of ESG classes, we recommend adding focus to the analysis by considering specific regions, more compact timeframes, and following the proposed methodology of building a model for each layer of analysis. We stand by and recommend the use of quantitative firm-level ESG scores for such analyses, ensuring robustness and replicability in models. As the availability of ESG information, awareness of ESG investing, and mandates on disclosure increase in the coming years, we hypothesize the study of ESG to have significant relevance in underpricing theory.

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