Do carbon emissions affect IPO price formation and aftermarket performance?

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Abstract

This paper explores the impact of carbon emissions on IPO price formation and aftermarket performance. The sample consists of 1,720 new issues that went public between January 2004 and December 2021, with 298 IPOs categorized in the Disclosure Group (covered by the Trucost database) and the remaining 1,422 in the Non-Disclosure Group. Our analysis yields several noteworthy and original findings. Firstly, new issuers with higher carbon emissions tend to have lower initial offer values and experience more negative price revisions. This suggests that underwriters discount brown IPOs to a greater extent, and institutional investors exhibit a disfavorable bias towards such IPOs. Furthermore, the discount and downward price revision on brown IPOs intensify with increased climate change concerns and post the Paris Agreement. Secondly, the total level or intensity of an issuer's carbon emissions does not significantly impact underpricing. Thirdly, new issuers with higher carbon emissions demonstrate higher long-run post-issue abnormal returns than those with lower carbon emissions. We conduct several auxiliary tests to verify the robustness of our results against concerns about endogeneity issues. Overall, our findings support the notion that investors demand higher expected returns to invest in shares of brown firms. Consequently, this leads to lower initial offer values, more negative price revisions, and higher long-run post-issue abnormal returns associated with higher carbon risks.

JEL: G14; G30; M14; Q51; Q53; Q54

Keywords: Carbon emissions; Initial public offerings; IPO price formation; Long-run performance

1. Introduction

Over the past two decades, an increasing body of evidence has emerged to corroborate global warming and its consequential impact on climate patterns. The repercussions of extreme weather events are significant loss of human lives and extensive economic damage. Carbon dioxide (CO_2) emissions, or greenhouse gas (GHG) emissions, stemming from human activities, stand out as one of the foremost drivers of climate change. Policies concerning restrictions and penalties on carbon emissions, as well as incentives for the development of new technologies to mitigate these emissions, hold the potential to influence the value and prosperity of firms profoundly. Numerous studies have been devoted to assessing whether carbon emissions represent a significant risk factor for cross-sectional stock returns and, if so, the direction of this effect. However, empirical findings on this matter remain inconclusive.

Pástor, Stambaugh, and Taylor (2021) put forth a theoretical framework to model the influence of sustainable investing and shifts in climate risks on asset prices. Their model posits two predictions regarding the relationship between carbon emissions and stock returns. Firstly, the model suggests that green assets are expected to yield lower returns than brown assets. This stems from the premise that investors derive greater utility from holding green assets than brown ones. Consequently, investors are willing to pay a premium for green assets, thereby reducing the cost of capital for green firms. In equilibrium, investors with a stronger inclination towards environmental, social, and governance (ESG) factors will allocate more of their portfolio to green and less to brown assets. Conversely, investors with weaker ESG preferences are inclined to hold more brown assets and fewer green assets, resulting in higher expected returns as a risk premium. Secondly, the model suggests that shocks of climate risk concerns will prompt shifts in investor preferences towards green assets and consumer preferences towards green products. This surge in demand for green assets will drive up their prices.

We validate the predictions of Pástor et al. (2021) by examining the impact of carbon emissions on IPO price formation, underpricing, and post-issue performance of new issues in the U.S. market. We argue that IPO bookbuilding settings offer four distinct advantages for such analysis. Firstly, during IPO price formation, the initial offer price determination incorporates assessments from the issuer and investment banks. If investors demand higher returns on brown IPOs as risk premiums, we anticipate that brown IPOs will debut with lower initial offer values than green IPOs. Analyzing IPO initial offer prices provides more intuitive insights than examining the equity market. Secondly, institutional investors' private information and valuations are solicited during the bookbuilding process roadshow. If institutional investors favor green assets and underwriters adjust the final offer price accordingly, we expect downward revisions for brown IPOs while green IPOs remain unaffected. The bookbuilding mechanism in the primary market uniquely reveals private information, unlike the secondary market.

Thirdly, new shares start trading in the aftermarket, allowing us to assess the initial and long-term performance of green and brown IPOs. Comparing the stock returns of brown and green IPOs in the aftermarket with returns in the secondary market, as prior research has focused on, provides valuable insights. Lastly, the concurrent availability of carbon emission and stock return data poses a challenge for existing studies focused on the secondary market (Zhang, 2023; Aswani et al., 2024a). Studying the impact of carbon emissions on stock returns in the secondary market necessitates simultaneous examination of numerous firm-level, historical carbon emission data provided by vendors. Conversely, in the primary market, the number of firms going public within an interval (e.g., a week) is limited. Suppose carbon emission is a significant factor influencing the valuation of new issues. In that case, such data becomes crucial in the IPO process, and underwriters and institutional investors will acquire data on carbon emission not only from vendors but also from other information sources, such as news reports, prospectuses, company interviews, roadshows, and due diligence. It means that the availability of concurrent data for examining the impact of carbon emissions on stock prices is less problematic for IPO stocks than for those already in the secondary market.

We examine the price formation, underpricing, and long-term performance of 1,720 U.S. IPOs launched from January 2004 to December 2021. Among them, 298 IPOs have carbon emission data available in the first IPO year, classified as the Disclosure Group, while the remaining 1,422 IPOs are classified as the Non-Disclosure Group. In addition to comparing IPO price formation and aftermarket performance between the two groups, we primarily focus on the impact of carbon emissions for the 298 IPOs in the Disclosure Group. Specifically, we explore the influence of carbon emissions on IPO price formation and aftermarket performance.

Our analysis yields several noteworthy findings. First, we examine the initial offer value and find that new issuers in the Disclosure Group have significantly lower initial offer values than IPOs in the Non-Disclosure Group. Furthermore, within the Disclosure Group, new issuers with higher carbon emissions have lower initial offer values. Suppose new issuers in the Non-Disclosure Group or those with low carbon emissions are considered green IPOs, while those in the Carbon Emission Group or with high carbon emissions are considered brown IPOs. In that case, our results suggest that issuers and underwriters discount brown issuers more than green issuers.

Second, one feature of bookbuilding conducive to discovering the intrinsic value of an IPO firm is the ability of underwriters to gather private information from institutional investors during the roadshow and adjust the final offer price accordingly. We examine price revisions for new issuers and find that brown IPOs experience significant downward price revisions. Even though brown IPOs have lower initial offer values than green IPOs, participating institutional investors reveal concerns about the valuation of brown IPOs during the roadshow. Consequently, underwriters downwardly revise the final offer price for brown IPOs. Combining the initial returns and price revision results, we find that carbon emission significantly impacts IPO price formation. We also find that discounts and downward price revisions on brown IPOs intensify with increasing climate change concerns and post the Paris Agreement. These findings align with the predictions of Pástor et al. (2021) that expected returns on brown assets are higher than those on green assets and with the findings of Matsumura et al. (2014) that brown firms tend to have lower valuations than green firms.

Third, we examine the underpricing of new issuers and find that underpricing in the Disclosure Group is not significantly different from that in the Non-Disclosure Group. Within the Disclosure Group, carbon emissions do not significantly affect underpricing either. This result suggests that carbon emissions do not influence the underpricing of IPOs.

Fourth, we examine the relationship between carbon emissions and long-term post-issue stock performance, which is informative for testing two competing hypotheses explaining stock returns in the secondary market. The carbon transition hypothesis posits that green firms outperform brown firms due to growing climate concerns. In contrast, the climate risk hypothesis argues that brown firms outperform green firms, attributing the outperformance to a risk premium to compensate investors holding brown firms with higher climate risk exposure than green firms. We find that firms with higher carbon emissions have significantly higher long-term post-issue performance. This result is consistent with the climate risk hypothesis and suggests that investors require a risk premium for holding brown IPOs.

Pástor et al. (2021) suggest that expected returns on green assets are lower than on brown assets. However, due to climate risk shocks, the realized returns of green assets outperform those of brown assets when the fear of climate risks is high. In a related study, Pástor et al. (2022) illustrate that the realized returns of green and brown assets (and their difference) may differ from expected returns. Our study reconciles both views from ex-ante and ex-post perspectives. We find that brown IPOs have lower initial offer values and more negative price revisions than green IPOs during the price formation stage, with the association becoming more pronounced post-Paris Agreement or increasing climate risk concerns. This finding confirms that investors in the primary market demand higher returns for investments in brown IPOs than in green IPOs. We also find higher post-issue returns for brown IPOs than green IPOs in the aftermarket. This finding indicates that brown IPOs experience higher risks than green IPOs, and investors demand higher returns. This risk premium on brown IPOs is reflected in lower initial offer values, downward price revisions, and higher long-term post-issue returns.

Our contribution to the literature is threefold. First, we contribute to the literature on incorporating issuers' value-relevant information into offer prices and aftermarket stock prices for bookbuilding IPOs. Loughran and McDonald (2013) examine the effect of tone in Form S-1s on offer prices and initial returns. Edwards et al. (2019) compare offer prices and initial returns between traditional IPOs and supercharged IPOs, where pre-IPO owners establish "tax receivable agreements" to share future tax benefits with new investors. Dambra et al. (2020) study the effect of pre-IPO tax-advantaged trusts on initial offer value, price revision, initial returns, and long-term performance. He et al. (2022) investigate an international sample of IPOs from 20 IFRS-adopting countries from 2005 to 2016 and find that reporting fair-value earnings influences the valuation process and post-issue long-term performance. We provide evidence that carbon emissions affect issuers' IPO price formation and long-term post-issue performance in the aftermarket.

Second, our study contributes to the literature on the effect of sustainability on IPO pricing and post-issue performance. Baker et al. (2021) explore the association between country-level ESG performance and firm-level IPO underpricing by examining an international sample of 7,446 IPOs from 36 countries. They document that IPOs in countries with better ESG government ratings experience lower underpricing than those with poor ratings, indicating that good country-wide ESG performance can effectively mitigate information asymmetry and, in turn, lower IPO underpricing in these countries. However, Baker et al. (2021) fail to provide firm-level evidence. To the best of our knowledge, our study is the first to examine how IPO market participants and investors incorporate firms' sustainability performance into the equity valuation process.

Third, our study contributes to the literature on the effect of environmental pollution on firm valuations and stock returns. Although the impact of environmental pollution on stock returns has been examined in the literature, the issue is still under debate. On the one hand, Hsu et al. (2023) explore the effects of industrial pollution on the cross-section of stock returns and find that highly polluting firms are more exposed to environmental regulation risk, and investors command a pollution premium as compensation. Bolton and Kacperczyk (2021, 2023) also document that brown firms have higher expected returns than green firms. In an earlier study, Matsumura et al. (2014) examine carbon emission data for S&P 500 firms and find a negative association between carbon emissions and firm value. On the other hand, Pedersen et al. (2021) and Zhang (2023) examine the impact of carbon emissions on stock returns and document that brown firms underperform green firms. Pástor et al. (2022) and Ardia et al. (2023) find that when climate change concerns rise, stock returns of green firms outperform those of brown firms. Ghoul et al. (2011) find that firms with better performance on corporate social responsibility tend to have lower costs of equity. Our study makes an incremental contribution by documenting that brown IPOs have lower valuations in the price formation process and higher stock returns in the aftermarket than green IPOs.

2. Sample and Data

2.1 Sample

We retrieve new issues in the U.S. market completed between January 1, 2004, and December 31, 2021, from the Securities Data Company (SDC) New Issues database. To refine our initial sample, we apply the following selection criteria, similar to those used by Loughran and McDonald (2013): (i) We exclude financial firms (SIC code 6000-6799), depository receipts, unit offerings, rights offerings, closed-end funds, trusts, and limited partnerships. (ii) We exclude foreign listings and duplicate IPOs from the same offer. (iii) Additionally, we exclude new issuers with an issuing price of less than $5 per share and firms without secondary market closing prices or financial data available in the year before the offering. We obtain stock prices from the University of Chicago Center for Research in Security Prices (CRSP) and financial data from Compustat. Our final sample comprises 1,720 IPOs.

Our study focuses on the effect of carbon emissions on IPO price formation, underpricing, and long-run performance. Therefore, the measurement of carbon emissions for IPO firms is essential. We collect data on carbon emissions from the Trucost database, a crucial data vendor providing information on corporate carbon and other greenhouse gas emissions. While the number of new issuers covered by Trucost is limited, we record the carbon emissions of new issuers in the first IPO year, resulting in a subsample of 298 IPOs. Consequently, we classify our sample into two groups: 298 IPOs in the Disclosure Group (new issuers in the first IPO year covered by Trucost) and the remaining 1,422 IPOs in the Non-Disclosure Group (new issuers without available emission data).

One might question the justification of inclusion in the Disclosure Group if the carbon emission data for new issuers in the first IPO year are available. For instance, Zhang (2023) highlights the issue regarding the release lag of carbon emission data, which may not be available to investors when determining the offering price or even when the new shares commence trading in the aftermarket. However, the availability of carbon emission data from Trucost is not the sole channel through which investors can access information on the environmental performance of new issuers. Recent reports suggest that IPO firms adopting ESG strategies can enjoy several advantages, including attracting the interest of key investors, enhancing competitiveness, and establishing credibility for ESG practices, thereby bolstering the IPO firm's reputation. We posit that new issuers have incentives to improve the transparency regarding their ESG policies to achieve ESG strategy goals. As previously discussed, investors can directly access information on environmental performance through news reports, IPO prospectuses, company interviews, roadshows, and due diligence. Thus, the costs incurred by investors and underwriters to acquire carbon emission data for IPO firms are likely not substantial.

We present the frequency distribution of IPOs in Table 1. Panel A illustrates the frequency distribution by cohort year. Hot new issuances cluster in 2004-2007, 2013-2015, and 2018 onwards. Interestingly, the number of IPOs in the Disclosure Group rises significantly after 2016, indicating that ESG transparency has become a crucial strategic consideration for IPOs in recent years. Notably, the Paris Agreement, a legally binding international treaty on climate change, was adopted by 196 parties at the UN Climate Change Conference (COP21) in Paris in December 2015.

<Table 1 is inserted about here>

Panel B of Table 1 presents the frequency distribution for new issuers' industries based on the Fama-French 49-industry (hereafter FF49) classification. Our IPO sample is notably concentrated in the Pharmaceutical Products industry (500 IPOs, constituting 29.1% of the total sample) and the Computer Software industry (311 IPOs, representing 18.1%). To delve deeper into the distribution of the Disclosure Group, while the Computer Software industry has the highest number of Disclosure IPOs (67 IPOs), the Construction Materials industry exhibits the highest proportion of IPOs classified in the Disclosure Group (6 out of 14 IPOs, accounting for 42.9% of total IPOs in this industry), followed by the Coal industry (40.0%) and the Machinery industry (39.1%). This observation is likely attributable to these industries being considered brown.

2.2 Firm and Deal Characteristics

Summary statistics for the Disclosure and Non-Disclosure Groups and their differences are provided in Table 2. Panel A presents statistics for firm characteristics of new issuers, while Panel B presents statistics for deal characteristics of IPOs. Detailed definitions of the variables can be found in Appendix A.

As shown in Panel A of Table 2, new issuers in the Disclosure Group exhibit larger sizes than those in the Non-Disclosure Group, as measured by assets and sales. The mean (median) assets of IPOs in the Disclosure Group amount to $1,552 million ($334 million), significantly higher than the mean assets of $462 million ($87 million) in the Non-Disclosure Group. Similarly, the mean (median) sales in the Disclosure Group total $1,099 million ($282 million), significantly surpassing the mean sales of $353 million ($63 million) in the Non-Disclosure Group.

<Table 2 is inserted about here>

Consistent with findings documented in Loughran and McDonald (2013), our sample of IPOs exhibits negative return on assets (ROA) in the year before going public. We observe that new issuers in the Disclosure Group tend to have relatively higher ROA (i.e., less negative ROA) than those in the Non-Disclosure Group. Additionally, while new issuers in the Disclosure Group allocate significantly less towards research and development expenditures (R&D) than those in the Non-Disclosure Group, the two groups have no significant difference in capital expenditures (CAPEX). The right-skewed and high variability in financial leverage contribute to a phenomenon where the Disclosure Group demonstrates a lower mean value of leverage but a higher median value than the Non-Disclosure Group. Moreover, fewer new issuers in the Disclosure Group receive backing from venture capital (VC) than those in the Non-Disclosure Group. In contrast, the proportion of IPOs backed by private equity (PE) funds exhibits the opposite trend.

As in Panel B of Table 2, new issuers in the Disclosure Group tend to have more proceeds and higher issuing prices than those in the Non-Disclosure Group. The fraction of shares sold by new issuers in the Disclosure Group is lower than that of the Non-Disclosure Group. Furthermore, a higher proportion of new issuers in the Disclosure Group are taken public by top-tier underwriters, audited by the top four auditing firms, and listed on the NYSE compared to the Non-Disclosure Group. The average lockup period in the Disclosure Group is slightly more extended than that in the Non-Disclosure Group, but the difference is negligible. Lastly, the average pre-issue market returns and volatilities do not significantly differ between these two groups.

2.3 IPO valuation and performance

The summary statistics for IPO valuation and performance are presented in Panel C of Table 2. Three methods are employed to measure IPO valuation in the bookbuilding process (Guo, Lev, and Zhou, 2005; Willenborg, Wu, and Yang, 2015; He et al., 2022). The first measure is the initial offer value, calculated as the midpoint of the initial price range multiplied by the number of post-IPO shares outstanding, divided by the first post-IPO book value of total assets. The mean (median) initial offer value for the Disclosure Group is 2.21 (1.79), significantly lower than the mean (median) value of 2.60 (2.34) for the Non-Disclosure Group. Univariate analysis reveals that brown IPOs have a lower initial offer value than green IPOs.

The second IPO valuation measure is price revision, calculated as the price change from the midpoint of the initial price range to the final offer price. The average price revision for the Disclosure Group is 0.07%, compared to -1.51% for the Non-Disclosure Group, with a significant difference between the two groups.

The third IPO valuation measure is the final offer value, computed as the offer price multiplied by the number of outstanding post-IPO shares divided by the total assets' first post-IPO book value. The mean (median) final offer value for the Disclosure Group is 2.21 (1.80), significantly lower than the mean (median) of 2.55 (2.31) for the Non-Disclosure Group. This result is expected as the price revision on the initial offer value influences the final offer value.

Lastly, underpricing and long-run post-issue abnormal returns are computed for IPO aftermarket performance. Underpricing is calculated as the first-day closing price in the

CRSP divided by the offer price minus one. Long-run performance is proxied by the 250-day, 500-day, and 750-day buy-and-hold abnormal returns from the first day close (variables BHAR250, BHAR500, and BHAR750, respectively), representing one-year, two-year, and three-year post-IPO performance. The abnormal return is computed as the buy-and-hold daily stock return on the new issuer less the buy-and-hold market daily return, proxied by the CRSP value-weighted market portfolio return.

Panel C of Table 2 indicates that the average (median) underpricing for the Disclosure Group is 24.1% (13.7%), significantly higher than 18.6% (9.4%) for the Non-Disclosure Group. Long-run post-IPO performance exhibits a right-skewed distribution, with the mean substantially greater than the median for both groups. Importantly, long-run post-IPO performance in the Disclosure Group surpasses that in the Non-Disclosure Group, with statistically and economically significant differences. For instance, the mean (median) BHAR250 for the Disclosure Group is 7% (-2%), compared to -10% (-21%) for the Non-Disclosure Group, indicating that investors holding brown IPOs in the aftermarket can realize higher abnormal returns than those holding green IPOs.

2.4 Summary statistics for carbon emission

We gather carbon emission measures for the Disclosure Group to investigate the relationship between carbon emissions and IPO pricing, initial return, and long-run post-issue performance. The Greenhouse Gas (GHG) Protocol categorizes emissions into three sources. Scope 1 emissions encompass GHG emissions produced directly by a firm, stemming from fossil fuel combustion or manufacturing releases. Scope 2 emissions represent indirect emissions from purchased energy and water usage. These are deemed "indirect" because another facility, such as a power station, generates the emissions. Scope 3 emissions encompass all other indirect emissions from customers (downstream) or suppliers (upstream) in the company's value chain. However, as these emissions occur beyond the firm's control, we exclude scope 3 emissions from our analysis following Pedersen, Fitzgibbons, and Pomorski (2021).

We incorporate four carbon emission variables in our empirical analyses: total levels of carbon scope 1 and scope 2 emissions and the intensities of carbon scope 1 and scope 2 emissions, respectively. Scope 3 emissions, being beyond the firm's control, are not included. We collect carbon emission data for new issuers in their first IPO year, with the unit for levels of carbon scope 1 and scope 2 emissions expressed as tons of CO2 equivalent. Prior studies, such as Matsumura et al. (2014) and Bolton and Kacperczyk (2021, 2023), have found total carbon emissions closely related to firm valuation and relevant in stock pricing. Conversely, Aswani, Raghunandan, and Rajgopal (2024a) and Zhang (2023) demonstrate that carbon intensity is more pivotal than unscaled carbon emission in explaining stock returns. Hence, we also gather the intensities of carbon scope 1 and 2 emissions to ensure robust results, with the unit for the intensity of carbon emissions expressed as tons of CO2 equivalent divided by the issuer's revenue in a million US dollars. The summary statistics for carbon emission variables are presented in Panel A of Table 3.

<Table 3 is inserted about here>

As depicted, the average production of scope 1 and scope 2 emissions for our 298 Disclosure IPOs is 101.7 thousand tons and 39.1 thousand tons equivalent, respectively. These figures suggest that, unsurprisingly, the new issuers in our sample emit considerably less greenhouse gas than established firms in the secondary market. For instance, the average firm in Bolton and Kacperczyk (2021) emits 1,970 thousand tons of scope 1 emissions and 342 thousand tons of scope 2 emissions. Notably, the distribution of scope 1 and scope 2 carbon emission levels exhibits a highly positive skew. Thus, to mitigate the influence of outliers on results, we take the natural logarithm of the carbon emission values in the empirical analysis.

Regarding carbon intensity, the average intensity of scope 1 emissions in our sample is 42.7 tons/million; for scope 2 emissions, it is 22.7 tons/million. We observe that the disparity in carbon emissions between new issuers in our sample and established firms in the secondary market diminishes when considering carbon emission intensities. For instance, Bolton and Kacperczyk (2021) report a mean intensity of 192 tons/million for scope 1 and 34 tons/million for scope 2.

Panel B of Table 3 presents the correlation matrix for the four measures of carbon emission variables. Carbon emission level is highly correlated with its carbon emission intensity. For instance, the coefficient between total scope 1 (2) emissions and their intensity measures is 0.664 (0.448). Furthermore, the two measures of carbon emissions are also highly correlated, with a coefficient of 0.605 between total scope 1 and scope 2 emissions and 0.437 between the two intensity measures. This suggests that firms producing more direct carbon emissions tend to make more indirect ones.

In addition to total carbon emission level and emission intensity, we construct tercile portfolios based on all firms' total carbon emissions and their carbon intensity. Specifically, we gather carbon emission data for universal Trucost U.S. firms and sort them into three groups from low to high within the 49 Fama-French industries each year. Based on these cut-off points, the 298 new issuers are assigned to tercile portfolios. The frequency distribution of portfolios and the summary statistics (mean and median) are presented in Panel C of Table 3.

The distribution of new issuers in portfolios formed by total carbon emission level differs significantly from those formed by carbon emission intensities. New issuers are predominantly clustered in portfolios with lower levels of total carbon emissions. For example, for scope 1 emissions, 190 new issuers are assigned to Portfolio 1, with only 45 in Portfolio 3, showing a monotonic decline from Portfolio 1 to Portfolio 3. Similar patterns are observed for scope 2 emissions. In contrast, the imbalance of IPOs in Portfolio 1 is alleviated for intensity measures. This discrepancy in distribution between total carbon emission level and emission intensity reflects the smaller operating scale of new issuers compared to established firms. While a smaller operating scale produces lower total carbon emissions, it does not necessarily result in lower carbon emission intensity if there is a correlation between a firm's sales and its total carbon emissions.

3. The impact of carbon emission on IPO price formation

We examine the influence of new issuers' carbon emissions on price formation by concentrating on the 298 IPOs within the Disclosure Group. As previously discussed, initial valuation and price revision are pivotal stages in the bookbuilding process.

3.1 The impact of carbon emissions on initial offer value

Prior research indicates that firms with higher carbon emissions often exhibit lower expected future cash flow and necessitate higher required returns (Pástor et al., 2021). Suppose issuers and underwriters consider the adverse effects of carbon emissions on pricing during valuation. In that case, we anticipate that firms with higher emissions (brown firms) will tend to have lower initial offer values than those with lower emissions (green firms). To explore this association, we calculate the mean and median values of initial offer prices for each portfolio categorized by carbon emission variables (as shown in Panel C of Table 3). The findings are detailed in Panel A of Table 4.

We observe that for total levels of carbon emissions, both the mean and median initial offer values demonstrate an inverse relationship with the carbon emission tercile portfolios. For instance, in portfolios sorted by the level of scope 1 carbon emissions, the mean (median) initial offer value in portfolio 1 is 2.44 (2.19), progressively declining to 1.41 (0.72) in portfolio 3. The differences in initial offer value between these portfolios are statistically and economically significant for both total levels of scope 1 and scope 2 carbon emissions.

<Table 4 is inserted about here>

Contrary to the findings regarding total carbon emission measures, the relationship between initial offer value and carbon emission intensity is less straightforward. While the mean and median values do not consistently decrease from low to high-intensity carbon emission portfolios, both intensity measures show a discernible downward trend. However, the differences in the mean and median initial offer values between the lowest and highest intensity carbon emission portfolios are generally insignificant, with only one exception being moderately significant.

The static analysis suggests that the two measures of the total carbon emissions directly impact the initial offer value. In contrast, the carbon emission intensity measures do not exhibit such a clear relationship. We conduct multivariate regression analysis to delve deeper into this relationship and account for other factors, such as deal and firm characteristics. In these regressions, the dependent variable is the initial offer value, and the independent variables include the carbon emission variable and other control variables commonly used in IPO literature to account for their effects on price formation, underpricing, and post-issue performance.

The regression results are reported in Panel B of Table 4. In regression (1), where the sample includes all 1,720 IPOs, we observe that the coefficient on the *Disclosure dummy* variable is -0.362 (with a t-statistic of -3.67), indicating that the initial offer value is set lower for new issuers in the Disclosure Group compared to the Non-Disclosure Group.

Moving on to regressions (2) to (5), where the sample includes only the 298 IPOs in the Disclosure Group, we find that the coefficients on the natural logarithms of the total level of scope 1 and scope 2 carbon emissions are significantly negative in regressions (2) and (3), respectively. For instance, the coefficient on *Ln (level of scope 1)* is -0.143, with a t-statistic of -2.54, suggesting that new issuers with higher carbon emissions have significantly lower initial offer values after controlling for firm and deal characteristics.

In regressions (4) and (5), where the independent variables of interest are the carbon emission intensity of scope 1 and scope 2, respectively, both coefficients are insignificantly negative. For example, the Intensity of scope 1 coefficient is -0.082 with a t-statistic of -1.36. Overall, the results from the multiple regressions of the initial offer value on carbon emissions suggest a negative impact of carbon emissions on the initial offer value. Underwriters and issuers appear to discount IPOs with higher carbon emissions more significantly. Moreover, the negative effects of carbon emissions seem more pronounced for the total levels of scope 1 and scope 2 carbon emissions. In contrast, the impact of the intensity measures is weaker. These multivariate analyses align generally with the findings from the univariate initial offer value analysis in tercile carbon emission portfolios.

3.2 The influences of carbon emissions on price revision

In the IPO roadshow, participating investors' interest in subscribing to new shares is elicited. When observing a positive signal from investors, the underwriter partially revises the offer price from the preliminary price range (Benveniste and Spindt, 1989; Benveniste and Wilhelm, 1990) upward. Otherwise, the underwriter tends to maintain the offer price at the lower price range or even revise the offer price downward. If institutional investors evade investing in brown firms, we would observe that new issuers with higher carbon emissions would have more negative price revisions. We conduct the regression analysis of price revision on carbon emissions and other control variables. The dependent variable is price revision, which is calculated as the price change from the midpoint of the initial price change to the final offer price. The regression results are reported in Table 5.

<Table 5 is inserted about here>

In the regression (1) of Table 5, the independent variable of interest is *Disclosure_dummy*, which equals one if the new issuer is in the Disclosure Group and equals zero otherwise. The sample includes all 1,720 new issuers. As reported, the coefficient is insignificantly negative, showing that price revision is not different between the Disclosure and Non-Disclosure Groups. We further focus on the 298 new issuers in the Disclosure Group. In regressions (2) to (5), the coefficients on all four carbon emission measures are significantly negative. For example, in regression (2), the coefficient on Ln (level of scope 1) is -2.28 (with a t-statistic of -5.09), and in regression (3), the coefficient on *Ln (level of scope 2)* is -2.93 (with a t-statistic of -5.12). The results indicate that underwriters revise the final offer price downward from the initial offer price for the new issuers with higher total levels of scope 1 and scope 2 carbon emissions. This suggests institutional investors may avoid investing in firms with higher carbon emissions, leading underwriters to revise offer prices downwards. It is noteworthy that we find a moderately negative coefficient on *the Intensity of scope 1* (in regression (4)) *and a significantly negative coefficient on the Intensity of scope 2* (regression (5)).

Based on the results from Table 5, we can attribute the downward price revision on brown IPOs to a disfavorable bias towards such IPOs. Pedersen et al. (2021) assert that institutional investors would incorporate ESG when forming their portfolios. They demonstrate that greener stocks will attract more institutional ownership in the subsequent period. Our results show that brown IPOs suffer more negative price revision in the bookbuilding mechanism, which is consistent with their views.

In the bookbuilding, the IPO price formation goes through the initial offer price and price revision. Therefore, it requests to integrate the results of Tables 4 and 5. The results in the two tables coherently conclude that underwriters set lower initial offer values and further revise downward more for the new issuers with higher carbon emissions. Therefore, this could lead to a negative association between the final offer value and carbon emissions. Indeed, the unreported results show negative coefficients on these four carbon emission measures.

3.3 The impact of climate risk concerns

The above analyses show that carbon emission has a negative impact on IPO price formation. Several actions, initiatives, and international treatments have been proposed against climate change in the past two decades by reducing greenhouse gas emissions. Among these efforts, the Paris Agreement is one of the most important international treaties on climate change. It is curious whether the negative impact of carbon emissions on IPO price formation has been more substantial in recent years, particularly after the Paris Agreement. Furthermore, environmental issues, such as the Deepwater Horizon catastrophe and the Volkswagen diesel scandal, have attracted public attention regarding environmental protection and climate change concerns. It is also curious whether the shocks to climate change concerns have boosted investors' demand for green financial assets in the primary markets. In this subsection, we address these two issues.

First, to examine whether the negative impact of carbon emission on IPO price formation is stronger in recent years, we add an interactive variable, in which the carbon emission variable interacts with Dummy_Paris, to the independent variables in the regressions of Tables 4 and 5. Dummy_Paris is an indicator equal to one if the IPO went public after adopting the Paris Agreement (December 2015). We re-estimate the regressions in Tables 4 and 5 and report the new results in Panel A of Table 6.

In Panel A, the dependent variable in the regressions (1) to (5) is the initial offer value. All of the coefficients on carbon emission variables are negative, but the interactive variables are positive. For example, in regression (2), the coefficient on Ln (scope1) is – 0.18 (with a t-statistic of – 3.17), and the coefficient on the interactive variable of Ln (scope1) with Dummy_Paris is 0.06 (t-statistic of 3.15). The results indicate that carbon emission has a negative impact on initial offer value, but the extent of carbon emission discounts has been mitigated after the Paris Agreement. It seems that underwriters do not further discount the carbon emissions of the new issuers when underwriters set the initial offer value. Price revision is the dependent variable in regressions (6) to (10). In contrast to the results in the initial offer value, all of the coefficients on the interactive variable are significantly negative. For example, in regression (7), the coefficient on Ln (scope1) is – 1.95 (with a t-statistic of – 4.33), and the coefficient on its interactive with Dummy_Paris is –0.52 (t-statistic of –3.34), showing that underwriters further downward price revision on brown IPOs post the Paris Agreement. The results also indicate that institutional investors have recently raised awareness of climate change, resulting in a more negative price revision post the Paris Agreement.

<Table 6 is inserted about here>

Second, to examine whether an increase in climate change concerns boosts investors' demand for green financial assets in the primary markets, we have to find the proxy for climate change concerns. Ardia et al. (2021) construct the Media Climate Change Concerns

Index (MCCC index) using data from eight major U.S. newspapers. They estimate an AR(1) model using the 36 months of the MCCC index data ending in month t-1. The MCCC_shock, which is the prediction error to month t's realization of MCCC minus the AR(1) model's prediction, is a shock to climate change concerns. The method is also employed by other related studies (e.g., Pástor et al. 2022). Following Ardia et al. (2021), we use MCCC_shock as a shock to climate change concerns. We add an interactive variable, in which the carbon emission variable interacts with MCCC_shock and one lag of MCCC_shock (MCCC_shock_lag1), to the independent variables in the regressions of Tables 4 and 5. We re-estimate the regressions in Tables 4 and 5 and report the new results in Panel B of Table 6.

As shown in Panel B, the dependent variable in the regressions (1) to (5) is the initial offer value. All coefficients on the carbon emission variables are significantly negative, but the coefficients on the interactive variables with MCCC_shock and MCCC_shock_lag1 are insignificantly or marginally positive. For example, in regression (2), the coefficient on Ln (scope 1) is – 0.15 (with a t-statistic of – 2.56), and the coefficient on its interactive variable Ln (scope1) × MCCC_shock is 0.019 (t-statistic = 0.62) and the coefficient on Ln (scope1) × MCCC_shock_lag1 is 0.029 (t-statistic=0.74). The findings suggest that underwriters and issuers do not discount the initial offer value more on brown IPOs when the climate change concerns heighten.

Price revision is the dependent variable in regressions (6) to (10). Interestingly, the coefficients on the interactive variables are negative, and some are statistically significant. For example, in regression (7), the coefficient on Ln (scope 1) is – 2.16 (with a t-statistic of – 4.70), the coefficient on interactive variable Ln (scope 1) × MCCC_shock is – 0.68 (t-statistic = – 2.30) and the coefficient on Ln (scope 1) × MCCC_shock_lag1 is – 0.28

(t-statistic = –1.01). The results indicate that institutional investors demand more green financial assets and less brown financial assets when climate change concerns are heightened, and thus, underwriters revise the downward price more on brown IPOs accordingly.

4. The influences of carbon emission on aftermarket performance

In the following two subsections, we will discuss the impact of carbon emission on aftermarket performance, including underpricing and long-run post-IPO performance.

4.1 The influences of carbon emission on underpricing

The earlier theoretical papers have documented that IPO underpricing compensates for ex-ante uncertainty and information asymmetry (Baron, 1982; Rock, 1986), and numerous studies have provided supporting evidence. For example, Ritter (1984), Beatty and Ritter (1986), and Ljungqvist and Wilhelm (2003) find that younger IPO firms, due to greater ex-ante uncertainty about the intrinsic value and a higher level of information asymmetry, have a higher level of initial returns. Loughran and McDonald (2013) examine the tone of Form S-1s and find that IPOs with higher levels of uncertain language experience a higher degree of underpricing. Megginson and Weiss (1991) document that VC-backed IPOs have less underpricing because VCs play a certification role. Hong, Hung, and Lobo (2014) find a decrease in country-level IPO underpricing following mandatory IFRS adoption and attribute the finding to reducing information asymmetry between issuers and investors.

Matsumura et al. (2014) find that firms that voluntarily disclose their carbon emissions have higher firm value than non-disclosure firms. They also document a negative association between carbon emission and firm value. It is curious to ask the questions whether new issuers in the Carbon Emission Group would have lower or higher information asymmetry and ex-ante uncertainty than those in the Other IPO Group and whether IPOs with higher carbon emissions have lower or higher information asymmetry and ex-ante uncertainty than those with lower emissions. We examine the influence of carbon emission on IPO underpricing and report the results in Table 7.

<Table 7 is inserted about here>

In regression (1), the independent variable of interest is *Disclosure_dummy,* which equals one if the new issuer is in the Disclosure Group and zero otherwise. The coefficient is insignificantly positive. It indicates that the underpricing of the new issuers in the Disclosure Group does not materially differ from that in the Non-Disclosure Group. In regressions (2) to (5), all of the coefficients on the carbon emission measures are not significantly different from zero. Overall, the results in Table 7 suggest neither the classification of new issuers in the two groups nor the level of carbon emission is related to the extent of information asymmetry and uncertainty about the pricing of intrinsic value.

4.3 The influences of carbon emissions on long-run post-issue performance

In this subsection, we conduct a multivariate analysis to examine the effect of carbon emissions on post-IPO long-run performance. Following the earlier discussions, because brown assets are exposed to climate risk, investors require a premium to invest in firms with high carbon emissions. The climate risk hypothesis hence predicts a positive relationship between carbon emissions and long-run performance. In contrast, the carbon transition hypothesis asserts a negative relationship between carbon emissions and stock returns because investors expect that the “greenium” (the difference between the expected returns of green and brown stocks) dominates the IPO firms. Therefore, such an investigation would help us determine which of the scenarios above is best supported by the data.

We use the 250-day (1-year), 500-day (2-year), and 750-day buy-and-hold post-IPO abnormal return (BHAR250, BHAR500, and BHAR750, respectively), which begins from the first-day close, to proxy for the long-run abnormal return. We start our empirical analysis by regressing the BHAR250 on the carbon emission and control variables and report the resorts in Panel A of Table 8. The regression results of BHA500 and BHAR750 are presented in Panels B and C of Table 8.

As shown in Panel A of Table 8, the coefficient on Disclosure_*dummy* is 0.18 (t-statistic＝3.74), which is statistically and economically significant. This implies that the average firms in the Disclosure Group outperform the Non-Disclosure Group in the 250 days (approximately one year) following the IPO by 17.7%.

<Table 8 is inserted about here>

Next, we analyze the effect of carbon emissions on the long-run performance of the Disclosure Group. In regression (2), the coefficient on *Ln (level of scope 1)* is 0.08 with a t-statistic of 3.48. Similarly, in the regressions (3), the coefficient on *Ln (level of scope 2)* is 0.11 (t-statistic = 3.76). The two regressions show that the total levels of carbon emissions, both scope 1 and scope 2, positively correlated with the BHAR250. It indicates that firms with higher carbon emissions have higher long-run post-issue abnormal returns. The finding is consistent with the view of the climate risk hypothesis that investors require a carbon risk premium to hold high carbon emission stocks.

On the other hand, the coefficients of the carbon emission intensity measures become slightly weaker in terms of statistical significance. The coefficient on the Intensity of scope 1 is 0.05 (with a t-statistic of 1.13), and on the Intensity of scope 2 is 0.35 (with a t-statistic of 1.67) is significant. The coefficient in regression (4) is insignificant, but the association between carbon emission intensity and long-run performance is still positive.

We further examine the BHAR500 and BHAR750 and find that the results of the positive impact of carbon emission on long-run performance are intact. The only exception is that the coefficient of the Intensity of scope 2 becomes statistically insignificant. Our findings support the climate risk hypothesis that investors require a carbon risk premium to hold the high carbon emission stocks and do not change materially when we use longer-term abnormal returns to proxy for long-run performance.

5. Robustness checks

One caveat of our analysis is that the Disclosure Group only accounts for a relatively low proportion of the total sample (about 17% of our sample observations are classified in the Disclosure Group). It is possible, therefore, that firms choose to disclose carbon emissions because of unobservable firm characteristics or because of the regulatory environment in which they operate and then, in turn, are classified in the Disclosure Group. It is also likely that brown companies, facing the carbon emission discount, may self-select to do IPO only if the benefits of going public are substantially higher than those of comparable green IPO. In other words, the decision to disclose carbon emissions may be endogenous or self-selected, and, as such, our sample of IPOs in the Disclosure Group is not drawn from a random sampling process. If this is the case, our estimates could suffer from sample selection bias. We perform two analyses to address this concern.

5.1 Heckman two-stage regression

As the first attempt to correct for potential sample selection bias, we re-estimate our regressions using a Heckman correction model (Heckman, 1976, 1979), which involves a two-stage estimation method. In our research setting, we aim to investigate the influences of carbon emissions on IPO price formation and aftermarket performance. Still, we can access the carbon emission observations only for those who disclose their carbon emission data. If the new issuers classified in the Disclosure Group are selected non-randomly from the IPO population, estimating the influences of carbon emissions on IPO price formation and aftermarket performance from the Disclosure Group may introduce bias. Hence, we employ the Heckman model to correct for non-randomly selected samples.

In the first stage, we specify a set of variables that explain the probability that a firm is classified in the Disclosure Group. We estimate this probit model using the entire sample of 1,720 IPOs. In the second stage, we estimate the regressions to investigate the impact of carbon emission measures on initial offer return, price revision, underpricing, and long-run performance using only those observations in the Disclosure Group.

To identify an exogenous determinant for the probability of being included in the Disclosure Group in the selection model, we consider the natural logarithm of sales (*Ln_sales*). Current literature has confirmed that carbon emissions are highly correlated to the firm's sales (Aswani et al., 2024a; Zhang, 2023). Moreover, larger firms are more likely to disclose carbon emissions (Matsumura, 2014). Hence, we expect a positive association between firms' sales and the likelihood of being included in the Carbon Emission Group. In addition to *Ln_sales*, we also include ten firm and deal characteristics (*Leverage*, *Tangibility, CAPEX, R&D*, *VC_backed*, *PE_backed*, *NYSE*, *Underwriter reputation*, and *ROA*) that are significantly different between the Disclosure Group and the Non-Disclosure Group (Table 2) in the selection equation.

To perform the selection equation in the Heckman model, we set a dummy variable of one if an IPO firm is included in the Disclosure Group and zero otherwise. We then estimate the selection equation using the Probit model with our whole sample and report the estimates in Panel A of Table 9. Not surprisingly, the coefficient of *Ln_sales* is positive with strong statistical significance. The finding is consistent with our conjecture that the larger firms in terms of sales are more likely to disclose their carbon emission and, in turn, be included in the Disclosure Group by our study. For the other control variables, we find that the coefficient on *R&D* is significantly positive, and the coefficient on *PE_backed* is marginally negative. The remaining control variables are not significant.

<Table 9 is inserted about here>

We then proceed to the estimates in the second stage: the influences of carbon emission on the initial offer value (the results are reported in Panel B of Table 8), price revision (Panel C), underpricing (Panel D), and long-run performance (Panel E), after controlling for the sample selection bias. The regressions in the second equation use only 298 new issuers classified in the Disclosure Group.

As shown in the Panel B of Table 8, the dependent variable in the second equation is the initial offer value. We find that a likelihood-ratio (LR) test of independent equations rejects the null hypothesis that the selection and regression equations are independent, and all coefficients on Inverse Mills' Ratio in columns (1) to (4) are highly significant. After correcting for selection bias, we document that the coefficients on four carbon emission variables are significantly negative. For example, the coefficient on *Ln (level of scope 1)* is -0.14 (with a t-statistic of -2.49), and the coefficient on Intensity of scope 1 is -0.11 (with a t-statistic of -1.74). More importantly, we compare the second-stage results in Panel B of Table 9 to regression results in Table 4 and continue to find that new issuers with higher carbon emissions have lower initial offer values.

In Panel C, the dependent variable in the second stage is price revision. We find that all coefficients on carbon emission measures in columns (1) to (4) are negative, and three of four coefficients are significant, suggesting that, after controlling for selection bias, the new issuers suffer more negative price revisions if they produce more carbon emissions. The values and significances of carbon emission measures are qualitatively similar to Table 5. In Panel D, the dependent variable is underpricing. None of the coefficients of carbon emission variables significantly differ from zero at the traditional level. Similarly, the findings are coherent with the results in Table 7.

Finally, the dependent variable in Panel E is BHAR250, a proxy for long-run performance. All coefficients on carbon emission variables are positive, and the coefficients on Ln (level of scope 1) and Ln (level of scope 2) are significantly different from zero.[1] Compared to the regression results in Table 8, the findings do not materially change.

To conclude the results in Table 9, after correcting for selection bias, we still find that carbon emission negatively impacts the initial offer value and price revision and positively affects the long-run performance. These results confirm that our findings do not suffer from sample selection bias.

5.2 Entropy balancing method

Our earlier examinations on the influences of carbon emissions on the IPO price formation, underpricing, and post-issue long-run performance document that carbon emissions play an important role. However, as reported in Table 2, differences exist in firm and deal characteristics between the Disclosure Group and Non-Disclosure Group. This could indicate that the Disclosure Group is not randomly assigned but is an endogenous choice that results in a bias in inference. It would be nice to have a sample formed through

[1] The results of BHAR500 and BHAR750 are qualitatively similar to the results of BHAR250. To save the space, we do not report the former two results. They are available upon request.

random experiments, and the estimates derived from the regression analysis should be unbiased (Rosenbaum and Rubin, 1983; Lee and Wahal, 2004). We construct a sample using a propensity score matching (PSM) procedure. Unfortunately, given significant differences in nearly all firm and deal characteristics between the Disclosure and Non-Disclosure Groups, finding a control group with a comparable characteristic similar to the treatment group is challenging. We employ the entropy balancing method to correct the endogenous bias.

The entropy balancing method is a multivariate reweighting method that directly calculates weights to adjust for the known sample distribution from the treatment and control groups (Hainmueller, 2012). The weights are used to construct the entropy-balanced sample such that the covariate distributions of treatment and control groups are similar regarding specified moment conditions. The regression estimates derived from the balanced sample should be unbiased to the extent that the entropy-balanced sample implements the covariate balance while retaining the efficiency for subsequent analyses. Following Dambra et al. (2020) and He et al. (2022), we employ the entropy balancing method to correct for the endogenous bias.

To construct the entropy-balanced sample, we perform the reweighting procedure separately for each of the initial offer values (Table 4), price revision (Table 5), underpricing (Table 7), and long-run regression (Table 8) regressions. Specifically, we reweigh our IPO sample such that no significant differences exist between the treatment group (firms in the Disclosure Group) and the control group (firms in the Non-Disclosure Group) for all control variables (all independent variables except carbon emission variables) at the first and second moments.[2] We then estimate the initial offer value, price revision, underpricing, and long-run performance regressions in the reweighted data. The results are reported in Table 10.

<Table 10 is inserted about here>

Panel A of Table 10 reports the entropy balance estimation of the initial offer value. The coefficient on the carbon emission variable is negative in all regressions. The coefficients on Ln (level of scope 1) and Ln (level of scope 2) significantly differ from zero. Panel B presents the estimation of the entropy balance of price revision. The coefficient on the carbon emission variable is negative in all regressions, and three coefficients are significantly different from zero; the only exception is the coefficient on the Intensity of scope 1. Overall, the entropy balance estimation confirms our findings that the negative impact of carbon emissions on IPO price formation is not sensitive to the non-random sampling problem.

Panel C of Table 10 represents the entropy balance estimation of underpricing. Not surprisingly, the coefficient on carbon emission is insignificant; the only exception is the one on Intensity of scope 2. Panel D of Table 10 reports the entropy balance estimation of BHAR250.[3] We find that all coefficients on carbon emission variables are significantly positive. For example, the coefficient on Ln (level of scope 1) is 0.022 (with a t-statistic of 4.20), and the coefficient on Intensity of scope 1 is 0.087 (with a t-statistic of 2.20). The results indicate that our findings support the climate risk hypothesis that investors require a carbon risk premium to hold the high carbon emission stocks and do not change

[2] The unreported analysis shows that there is no statistically significant difference in these independent variables between the control and the treatment groups in the first and second moment. The result is available upon request.
[3] The unreported results on the entropy balance estimation of BHAR500 and BHAR750 are qualitatively similar to the ones of BHAR250. These results are available upon request.

materially when we use the entropy-balanced sample.

Consistent with the main results, the effect of carbon emission is sustained using the entropy-balanced method. We continue to find that carbon emission negatively impacts the initial offer value and price revision and positively affects the long-run performance. As such, we conclude that our results are not sensitive to the non-random sampling problem.

6. Justification of carbon emission data

We categorize our sample into two groups based on whether new issuers in their first IPO year are covered by Trucost: 298 IPOs in the Disclosure Group and the remaining 1,422 IPOs in the Non-Disclosure Group. We further focus on the Disclosure Group to analyze the impact of the total level of carbon emissions or the carbon emission intensity on IPO price formation and aftermarket performance. We presume and document that IPOs in the Non-Disclosure Group are greener than IPOs in the Disclosure Group, and IPOs with lower carbon emissions are greener than those with higher emissions. In this section, we conduct calendar-time portfolio regressions to substantiate our presumptions.

We construct four post-IPO portfolios: Non-Disclosure, Port1, Port2, and Port3. The Non-Disclosure portfolio consists of IPOs in the Non-Disclosure Group. Port1, Port2, and Port3 are three portfolios classified by the total level of scope 1 carbon emissions reported in Panel C of Table 3. Each calendar-time portfolio includes two years of post-IPO monthly returns, beginning from the close of the first IPO month.

Next, we calculate the green-minus-brown (GMB) returns using universal Trucost U.S. firms. Specifically, we gathered carbon emission data for universal Trucost U.S. firms and sorted them into three portfolios from low to high within the 49 Fama-French industries each year. Then, we calculate the equally weighted monthly returns for these three portfolios. GMB monthly return is computed as the portfolio return of low carbon emission firms minus the portfolio return of high carbon emission firms. We then conduct time-series regressions using Fama-French three-factor returns plus GMB, the green-minus-brown monthly return. We ran the regression of excess return (IPO portfolio return minus risk-free return) on the RMRF, SMB, HML, and GMB. The regression results are reported in Table 11.

<Table 11 is inserted about here>

As depicted in Table 11, in the regression of Non-Disclosure IPOs, the coefficient on GMB is significantly positive at 0.325 (with a t-statistic of 1.78). The positive factor loading on GMB suggests that Non-Disclosure IPOs are more inclined to behave as green stocks in the aftermarket. However, the coefficients on GMB in the regressions of Portfolios 1 and 2 are insignificant, indicating that IPOs in these two portfolios may have some, but not significant, concerns regarding carbon emissions. In contrast, in the regression of Portfolio 3, the coefficient on GMB is significantly negative. This negative factor loading on GMB suggests that IPOs in Portfolio 3 are likelier to behave as brown stocks in the aftermarket. The findings in Table 11 align with our empirical results and support our presumptions.

7. Conclusion

Scientists and policymakers have discussed the causes and consequences of climate change over several decades. Carbon dioxide (CO_2) or greenhouse gas (GHG) emission from human activities is one of the most important drivers of climate change. The goal of several initiatives, such as the Kyoto Protocol and the Paris Agreement, is to reduce carbon and greenhouse gas emissions. Extant literature examines the association of carbon emissions on firm valuation and stock returns. They provide pioneer evidence to support the argument that firms' carbon emissions have material influences on firm value and stock returns. However, all of the research focuses on the secondary market, and the research on the association between carbon emission and stock returns has divergent views. To fill the literature gap, we explore the carbon emissions of the new issuers and investigate the impact of carbon emissions on IPO price formation (including initial offer value and price revision), underpricing, and long-run post-issue performance.

Our sample includes 1,720 IPOs that went public from January 2004 to December 2021. Among them, 298 new issuers disclose their carbon emission data in the IPO year and thus are included in the Disclosure Group; the remaining 1,422 new issuers are classified as the Non-Disclosure Group. We find that new issuers in the Disclosure Group have lower initial offer values and more negative price revisions than the new issuers in the Non-Disclosure Group. Furthermore, new issuers emitting more carbon dioxide have lower initial offer values and more negative revisions than those emitting less carbon dioxide. The findings indicate that the investment bankers and institutional investors in the primary markets discount the valuation more for brown IPOs. We also find that institutional investors have raised awareness of climate change in recent years and heightened climate risk concerns, resulting in a more negative price revision post the Paris Agreement and the shocks to climate change concerns. Finally, the new issuers in the Disclosure Group have higher long-run post-issue performance than new issuers in the Non-Disclosure Group. Furthermore, among the IPOs in the Disclosure Group, the long-run performance is positively associated with carbon emissions. Overall, the presented empirical results suggest that investors require higher returns as compensation to hold the shares with higher carbon risks.

In general, our results show that because investors disfavor brown IPOs, they require higher returns as compensation to invest in new issuers with higher carbon emissions. Underwriters thus set lower initial offer values to offer more discounts for the brown IPOs. In the aftermarket, because the brown IPOs have been discounted in the offer price, their post-issue abnormal return is higher than green IPOs. Our findings are consistent with the climate risk hypothesis that a higher return on brown IPOs is a risk premium to compensate for higher climate risk.

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Table 1 Frequency Distribution of IPOs

This table reports the frequency distribution of IPOs in the U.S. equity market from January 2004 to December 2021. The initial sample is obtained from the Securities Data Company (SDC) New Issues database. We exclude financial firms (SIC code 6000-6799), depository receipts, unit offerings, rights offerings, closed-end funds, trusts, and limited partnerships. We exclude foreign listings, duplicate IPOs from the same offer, issuing prices less than $5 per share, and firms without secondary market closing prices or financial data available the year before the offering. The final sample comprises 1,720 IPOs. We divide all IPOs into two groups, Disclosure and Non-Disclosure IPOs, based on whether Trucost covers the new issuers in the first IPO year. Panel A reports the frequency distribution of IPOs by cohort year; Panel B presents the frequency distribution by issuers' industry (using the Fama-French 49-industry classification).

Panel A: The frequency distribution of IPOs by cohort year

Cohort Year	Disclosure	Non-Disclosure	Total number of IPOs
2004	6	103	109
2005	10	85	95
2006	8	102	110
2007	7	117	124
2008	1	16	17
2009	5	27	32
2010	1	58	59
2011	4	48	52
2012	5	66	71
2013	15	94	109
2014	5	136	141
2015	14	77	91
2016	41	18	59
2017	51	30	81
2018	48	63	111
2019	13	80	93
2020	43	82	125
2021	21	220	241
Total	298	1,422	1,720

Panel B: The frequency distribution of IPOs by industry

FF49 industry	Disclosure	Non-Disclosure	Total number of IPOs
Agriculture	1	2	3
Food Products	4	11	15
Candy & Soda	0	3	3
Beer & Liquor	0	6	6
Tobacco Products	1	0	1
Recreation	4	7	11
Entertainment	4	20	24

Printing and Publishing	0	4	4
Consumer Goods	3	15	18
Apparel	1	10	11
Healthcare	7	32	39
Medical Equipment	13	92	105
Pharmaceutical Products	57	443	500
Chemicals	5	15	20
Rubber and Plastic Products	1	3	4
Construction Materials	6	8	14
Construction	1	12	13
Steel Works Etc	0	7	7
Fabricated Products	0	3	3
Machinery	9	14	23
Electrical Equipment	3	13	16
Automobiles and Trucks	2	9	11
Aircraft	1	3	4
Shipbuilding, Railroad Equipment	0	5	5
Defense	0	2	2
Precious Metals	0	2	2
Non-Metallic and Industrial Metal Mining	0	3	3
Coal	2	3	5
Petroleum and Natural Gas	14	37	51
Utilities	4	7	11
Communication	7	19	26
Personal Services	2	16	18
Business Services	22	62	84
Computers	4	22	26
Computer Software	67	244	311
Electronic Equipment	12	58	70
Measuring and Control Equipment	2	15	17
Business Supplies	0	5	5
Transportation	5	22	27
Wholesale	8	25	33
Retail	19	62	81
Restaurants, Hotels, Motels	5	35	40
Other	2	46	48
Total	298	1,422	1,720

Table 2 Summary Statistics for Disclosure and Non-Disclosure IPOs

The sample includes 1,720 U.S. IPOs that went public between January 2004 and December 2021. We partition all IPOs into Disclosure (298 IPOs) and Non-Disclosure (1,422 IPOs) groups and provide summary statistics for the two groups and statistics of differences between them. We present the summary statistics for firm characteristics of issuers in Panel A, deal characteristics of IPOs in Panel B, and IPO valuation and performance in Panel C. Variable definitions are provided in Appendix A. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% level, respectively.

	Disclosure			Non-Disclosure			Difference	
	Mean	Std Dev	Median	Mean	Std Dev	Median	t-stst.	z-stat.
Panel A: Firm characteristics of issuers								
Assets ($million)	1,552	2,593	334	462	1,131	87	7.12***	9.43***
Sales ($million)	1,099	1,929	282	353	926	63	6.52***	8.28***
ROA(%)	-19.81	56.82	-3.62	-45.43	103.76	-12.57	5.97***	3.44***
R&D (%)	19.51	51.81	0.64	38.85	70.44	1.58	-5.47***	-3.31***
CAPEX (%)	21.92	35.88	6.50	23.42	37.60	5.77	0.63	0.89
Leverage (%)	37.08	41.29	30.41	40.98	62.45	22.35	-1.34	1.69*
Tangibility (%)	19.91	22.51	11.48	16.27	20.77	8.08	2.57**	2.93***
VC-backed	0.47	0.50	0.00	0.55	0.50	1.00	-2.44**	-2.43**
PE-backed	0.35	0.48	0.00	0.26	0.44	0.00	2.94***	3.09***
Panel B: Deal characteristics of IPOs								
Proceeds ($million)	473	605	222	212	291	116	7.28***	9.17***
Price	19.03	10.93	17.00	14.92	7.56	14.50	6.20***	7.56***
Fraction sold	0.30	0.23	0.22	0.32	0.19	0.27	-1.46	-4.33***
Underwriter reputation	0.91	0.28	1.00	0.78	0.41	1.00	6.74***	5.24***
Auditor reputation	0.87	0.34	1.00	0.79	0.41	1.00	3.22***	2.88***
Bookbuilt	1.00	0.00	1.00	1.00	0.06	1.00	1.22	1.12
Firm commitment	1.00	0.00	1.00	1.00	0.06	1.00	1.02	1.02
NYSE	0.44	0.50	0.00	0.25	0.43	0.00	6.27***	6.79***
Lockup	0.99	0.10	1.00	0.99	0.12	1.00	0.71	0.63
Market momentum (%)	1.65	1.88	1.70	1.63	1.85	1.69	0.15	0.34
Market volatility (%)	0.76	0.37	0.65	0.80	0.39	0.71	-1.59	-1.53
Panel C: IPO valuation and performance								
Initial offer value	2.21	1.56	1.79	2.60	1.49	2.34	-4.13***	-4.08***
Price revision (%)	0.07	12.38	0.00	-1.51	13.31	0.00	1.89*	2.18**
Final offer value	2.21	1.59	1.80	2.55	1.47	2.31	-3.43***	-3.44***
Underpricing	24.11	38.80	13.69	18.59	41.28	9.38	2.12**	2.18**
BHAR250	0.07	0.66	-0.02	-0.10	0.62	-0.21	4.30***	4.46***
BHAR500	0.15	1.10	-0.08	-0.13	0.87	-0.35	4.12***	3.18***
BHAR750	0.24	1.54	-0.25	-0.17	1.06	-0.47	4.43***	2.55**

Table 3 Summary Statistics for carbon emission variables and portfolios

This table reports summary statistics for the carbon emission variables and the frequency distribution of portfolios sorted by carbon emission variables. The sample includes 298 U.S. IPOs in the Disclosure Group, which went public between January 2004 and December 2021. Four carbon emission variables are used in the empirical analyses: total levels of carbon scope 1 and scope 2 emissions and the intensities of carbon scope 1 and scope 2, respectively. We collect the four carbon emission variables for the universal Trucost U.S. firms and rank them into tercile portfolios for each of the 49 Fama-French industries annually. We apply the cut-off points to 298 IPOs and classify them into tercile portfolios based on the four carbon emission variables. IPOs with the lowest (highest) level or intensity of carbon emission are assigned in Portfolio 1 (3). Panel A reports descriptive statistics of the issuers for the four carbon emission variables. The unit for levels of carbon emissions scope is expressed as tons of CO_2 equivalent, and the unit for the intensity of carbon emissions is expressed as tons of CO2 equivalent divided by the issuer's revenue in a million US dollars. Panel B provides the Person correlation coefficients for the four carbon emission variables. Panel C reports the frequency of tercile portfolios and summary statistics for the four carbon emission variables.

Panel A: Summary statistics for carbon emission variables

Carbon emission variables	Mean	Std Dev	Q1	Median	Q3
Level of scope 1 (tons CO_2e)	101,697	363,354	647	2,422	23,502
Level of scope 2 (tons CO_2e)	39,178	97,241	1,047	4,234	28,781
Intensity of scope 1 (tons CO_2e/USD m.)	42.68	104.00	5.13	13.46	21.07
Intensity of scope 2 (tons CO_2e/USD m.)	22.74	18.52	8.84	16.86	30.16

Panel B: Correlation matrix for carbon emission variables

Emissions	Level of scope 1	Level of scope 2	Intensity of scope 1	Intensity of scope 2
Level of scope 1	1.000			
Level of scope 2	0.605	1.000		
Intensity of scope 1	0.664	0.228	1.000	
Intensity of scope 2	0.364	0.448	0.437	1.000

Panel C: Frequency distribution of portfolios sorted by carbon emission variables and summary statistics

Portfolios sorted by		Portfolio 1 (low)	Portfolio 2	Portfolio 3 (high)	Total
	NOBS	190	63	45	298
Level of scope 1 (tons CO2e)	Mean	35,562	100,247	382,962	
	Median	1,072	4,411	45,385	
	NOBS	175	89	34	298
Level of scope 2 (tons CO2e)	Mean	10,241	39,948	186,100	
	Median	1,430	10,537	89,555	
	NOBS	129	92	77	298
Intensity of scope 1 (tons CO2e/USD m.)	Mean	25.74	44.70	68.65	
	Median	8.30	13.77	21.64	
	NOBS	112	90	96	298
Intensity of scope 2 (tons CO2e/USD m.)	Mean	14.61	22.58	32.38	
	Median	11.26	16.36	24.15	

Table 4 The influences of carbon emissions on initial offer value

This table presents the influences of carbon emissions on initial offer value, calculated as the midpoint of the initial price range multiplied by the number of post-IPO shares outstanding, divided by the first post-IPO book value of total assets. The sample includes 1,720 U.S. IPOs that went public between January 2004 and December 2021. We partition all IPOs into Disclosure (298 IPOs) and Non-Disclosure (1,422 IPOs). Four carbon emission variables are used in the empirical analyses: total levels of carbon scope 1 and scope 2 and the intensities of carbon scope 1 and scope 2, respectively. We construct three portfolios based on the above carbon emission variables individually. Firms with the lowest (highest) total level or intensity of carbon emission are assigned in Portfolio 1 (3). Panel A reports the summary statistics for the initial offer value of three carbon emission portfolios. Panel B presents the regression results of the initial offer value on carbon emissions. Regression (1) includes 1,720 IPOs, and the Disclosure_dummy is an indicator that equals one if the IPO is in the Disclosure Group. Regressions (2) to (5) include 298 Disclosure IPOs. Standard errors are clustered at the industry and year levels, and t-statistics are reported in parentheses. Variable definitions are provided in Appendix A. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% levels, respectively.

Panel A: The summary statistic of initial offer value for carbon emission portfolios

		Initial offer value				
Portfolio formed by		Portfolio 1	2	Portfolio 3	Difference (Port1-Port3)	Statistic
Level of scope 1	Mean	2.444	2.068	1.405	1.039	4.96 ***
	Median	2.190	1.392	0.723	1.467	3.77 ***
Level of scope 2	Mean	2.414	2.126	1.362	1.052	4.75 ***
	Median	2.190	1.246	0.677	1.512	2.96 ***
Intensity of scope 1	Mean	2.253	2.407	1.895	0.358	1.74 *
	Median	1.769	1.950	1.266	0.503	0.72
Intensity of scope 2	Mean	2.414	2.044	2.121	0.293	1.35
	Median	2.129	1.427	1.787	0.342	1.39

Panel B: The regression results of carbon emission measures on initial offer value

Independent variables	Dependent variable = Initial offer value				
	(1)	(2)	(3)	(4)	(5)
Disclosure_dummy	-0.362 ***				
	(-3.67)				
Ln (level of scope 1)		-0.143 **			
		(-2.54)			
Ln (level of scope 2)			-0.151 **		
			(-2.15)		
Intensity of scope 1				-0.082	
				(-1.36)	
Intensity of scope 2					-0.609
					(-1.21)
Ln (Proceeds)	0.579 ***	0.653 ***	0.686 ***	0.486 ***	0.499 ***
	(12.20)	(7.01)	(6.09)	(6.78)	(6.79)
Leverage	0.224 ***	0.240	0.264	0.151	0.154
	(2.70)	(0.88)	(0.96)	(0.52)	(0.55)
Tangibility	-0.315 *	0.629 *	0.256	0.269	0.209
	(-1.70)	(1.90)	(0.79)	(0.75)	(0.57)
CAPEX	-0.032 **	-0.061 *	-0.056 *	-0.029	-0.031
	(-2.09)	(-1.78)	(-1.78)	(-1.32)	(-1.31)
R&D	-0.001	-0.001	-0.002	-0.001	-0.000
	(-0.29)	(-0.37)	(-0.51)	(-0.27)	(-0.12)
Fraction sold	-2.938 **	-2.788 ***	-2.818 ***	-2.827 ***	-2.811 ***
	(-9.27)	(-8.57)	(-8.52)	(-8.71)	(-8.72)
VC-backed	1.044 ***	1.647 ***	1.685 ***	1.731 ***	1.733 ***
	(9.93)	(7.63)	(8.08)	(7.93)	(8.10)
PE-backed	-0.301 ***	-0.094	-0.087	-0.213	-0.173
	(-2.60)	(-0.48)	(-0.41)	(-1.05)	(-0.82)
NYSE	-0.462 ***	-0.315 **	-0.319 **	-0.357 **	-0.377 **
	(-4.47)	(-2.15)	(-2.14)	(-2.36)	(-2.50)
Underwriter reputation	-0.424 ***	-0.252	-0.267	-0.276	-0.287
	(-4.53)	(-0.72)	(-0.76)	(-0.80)	(-0.83)
Auditor reputation	-0.030	-0.043	-0.053	-0.133	-0.115
	(-0.29)	(-0.23)	(-0.29)	(-0.71)	(-0.61)
ROA-positive	3.038 ***	3.213 ***	3.328 ***	2.595 **	2.730
	(5.58)	(2.77)	(2.65)	(2.13)	(2.15)
ROA-negative	-0.488 ***	-0.279	-0.285	-0.327	-0.351 ***
	(-6.59)	(-1.31)	(-1.36)	(-1.28)	(-1.40)
Market momentum	1.216	-4.058	-4.100	-2.998	-2.797
	(0.43)	(-0.85)	(-0.87)	(-0.64)	(-0.61)
Market volatility	2.911	-1.098	-1.237	-1.021	-0.886
	(1.50)	(-0.32)	(-0.38)	(-0.31)	(-0.28)
FF49 industry dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Number of observations	1,720	298	298	298	298
Adj-R^2	0.810	0.806	0.805	0.799	0.800

Table 5 The influences of carbon emissions on price revision

This table presents the regression results of carbon emissions on price revision. The sample includes 1,720 new issues that went public between January 2004 and December 2021, of which 298 IPOs are classified in the Disclosure Group. The dependent variable is price revision, which is the price change from the midpoint of the initial price range to the offer price in the IPO. Regression (1) includes 1,720 IPOs, and the Disclosure_dummy is an indicator equal to one if the IPO is in the Disclosure Group. Regressions (2) to (5) include 298 Disclosure IPOs and four carbon emission variables used in the empirical analyses: total levels of carbon scope 1 and scope 2, and the intensities of carbon scope 1 and scope 2, respectively. Ln (level of scope 1) and Ln (level of scope 2) are the natural logarithm of the total levels of carbon scope 1 and scope 2, respectively. Variable definitions are provided in Appendix A. Standard errors are clustered at the industry and year levels, and p-values are reported in parentheses. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = Price revision				
Independent variables	(1)	(2)	(3)	(4)	(5)
Disclosure_dummy	-0.465				
	(-0.48)				
Ln (level of scope 1)		-2.284 ***			
		(-5.09)			
Ln (level of scope 2)			-2.927 ***		
			(-5.12)		
Intensity of scope 1				-1.290 *	
				(-1.78)	
Intensity of scope 2					-10.983 ***
					(-2.67)
Ln (Proceeds)	1.858 ***	3.762 ***	4.957 ***	1.098	1.325 *
	(4.58)	(4.35)	(4.91)	(1.41)	(1.67)
Leverage	-2.356 ***	-1.580	-0.887	-2.999 **	-3.001 **
	(-3.15)	(-1.03)	(-0.56)	(-2.11)	(-2.07)
Tangibility	-4.148 **	-0.273	-5.442	-6.049 *	-6.591 *
	(-2.37)	(-0.07)	(-1.52)	(-1.74)	(-1.74)
CAPEX	0.265 *	0.517	0.481	1.027 **	0.970 **
	(1.75)	(1.14)	(1.03)	(2.23)	(2.11)
R&D	-0.058 ***	-0.138 **	-0.146 **	-0.129 **	-0.118 **
	(-2.74)	(-2.35)	(-2.41)	(-2.35)	(-2.23)
Fraction sold	-9.342 ***	-1.989	-2.448	-2.609	-2.331
	(-4.93)	(-0.79)	(-0.94)	(-0.95)	(-0.87)
VC-backed	-1.281	-3.484 *	-3.119	-2.152	-2.160
	(-1.08)	(-1.65)	(-1.48)	(-0.98)	(-0.98)
PE-backed	-5.144 ***	-3.518 *	-2.997	-5.405 **	-4.698 **
	(-5.18)	(-1.73)	(-1.45)	(-2.47)	(-2.14)
NYSE	0.595	1.080	1.146	0.405	0.048
	(0.66)	(0.59)	(0.66)	(0.21)	(0.03)
Underwriter reputation	-0.148	3.664	3.501	3.271	3.113
	(-0.12)	(0.97)	(0.95)	(0.83)	(0.80)
Auditor reputation	-2.744 ***	-2.100	-1.958	-3.540	-3.189
	(-2.65)	(-0.88)	(-0.83)	(-1.54)	(-1.44)
ROA-positive	1.373	4.883	9.336	-4.990	-2.467
	(0.34)	(0.55)	(1.02)	(-0.57)	(-0.28)
ROA-negative	0.550	0.468	0.511	-0.296	-0.741
	(1.33)	(0.36)	(0.34)	(-0.38)	(-0.91)
Market momentum	34.931	59.379	54.493	76.307	79.630 *

	(1.54)	(1.36)	(1.30)	(1.57)	(1.69)
Market volatility	-14.455	-5.177	-8.077	-3.948	-1.486
	(-0.88)	(-0.28)	(-0.44)	(-0.18)	(-0.07)
FF49 industry dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Number of observations	1,720	298	298	298	298
Adj-R^2	0.074	0.136	0.152	0.050	0.067

Table 6 The influences of carbon emissions on price formation: The effect of the Paris Agreement and climate risks

This table analyzes the effect of Paris (in Panel A) and the climate change concerns (in Panel B) on the influences of carbon emissions on offer price formation: initial offer value and price revision. The sample includes 1,720 new issues that went public between January 2004 and December 2021, of which 298 IPOs are classified in the Disclosure Group. In both Panels, the dependent variable in regressions (1) to (5) is the initial offer value, and in regressions (6) to (10) is price revision. In regressions (1) and (6), the independent variables include Disclo_dum (Disclosure_dummy), which is an indicator equal to one if the IPO is in the Disclosure Group. Ln(scope1) in regressions (2) and (7) is the natural logarithm of the total levels of carbon emission scope 1. Ln(scope2) in regressions (3) and (8) is the natural logarithm of carbon emission scope 2. Intensity 1 in regressions (4) and (9) is the intensity of carbon emission scope 1, and Intensity 2 in regressions (5) and (10) is the intensity of scope 2. The independent variables include the interactive carbon emission variables with Dummy_Paris, or MCCC and MCCC_lag1, and other control variables in Tables 4 and 5. Dummy_Paris is an indicator equal to one if the IPO went public after the Paris Agreement (December 2015). MCCC_shock measures concerns about climate change with the Media Climate Change Concerns index documented in Ardia et al. (2021). MCCC_shock_lag1 is one-period lag of MCCC_shock. Variable definitions are provided in Appendix A. Standard errors are clustered at the industry and year levels, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% levels, respectively.

Panel A: Paris Agreement

	Dependent variable = Initial offer value					Independent variable = Price revision				
Var =	Disclo_dum.	Ln(scope1)	Ln(scope2)	Intensity 1	Intensity 2	Disclo_dum.	Ln(scope1)	Ln(scope2)	Intensity 1	Intensity 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Var	-0.940 ***	-0.182 ***	-0.208 ***	-0.112 *	-1.181 **	1.861	-1.946 ***	-2.538 ***	-0.444	-2.125
	(-4.60)	(-3.17)	(-3.08)	(-1.83)	(-2.44)	(1.35)	(-4.33)	(-4.37)	(-0.51)	(-0.44)
Var*Dummy_Paris	0.721 ***	0.061 ***	0.068 ***	0.101	1.007 *	-2.906 *	-0.528 ***	-0.464 ***	-2.845 **	-15.598 ***
	(3.28)	(3.15)	(3.27)	(0.92)	(1.93)	(-1.75)	(-3.34)	(-2.89)	(-2.49)	(-3.07)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FF49 industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,720	298	298	298	298	1,720	298	298	298	298
Adj-R^2	0.812	0.813	0.813	0.799	0.802	0.075	0.073	0.169	0.063	0.091

Panel B: Climate change concerns

Var =	Dependent variable = Initial offer value					Independent variable = Price revision				
	Disclo.dum	Ln(scope1)	Ln(scope2)	Intensity 1	Intensity 2	Disclo_dum.	Ln(scope1)	Ln(scope2)	Intensity 1	Intensity 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Var	-0.396 ***	-0.148 **	-0.158 **	-0.161 **	-0.787	0.217	-2.160 ***	-2.828 ***	-0.682	-9.064 **
	(-3.95)	(-2.56)	(-2.23)	(-2.54)	(-1.51)	(0.24)	(-4.70)	(-4.92)	(-0.56)	(-2.10)
Var*MCCC_shock	0.146	0.019	0.016	0.315 *	1.184	-6.583 **	-0.678 **	-0.709 **	-3.197	-16.086
	(0.50)	(0.62)	(0.49)	(1.68)	(0.95)	(-2.52)	(-2.30)	(-2.55)	(-0.98)	(-1.50)
Var*MCCC_shock_lag1	0.259	0.029	0.032	0.335 *	0.834	-2.959	-0.279	-0.227	-1.927	-7.923
	(0.99)	(0.74)	(0.85)	(1.89)	(0.81)	(-1.29)	(-1.01)	(-0.76)	(-0.52)	(-0.81)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FF49 industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,714	298	298	298	298	1,714	298	298	298	298
Adj-R^2	0.810	0.806	0.804	0.799	0.800	0.077	0.146	0.164	0.047	0.069

Table 7 The influences of carbon emissions on underpricing

This table presents the regression results of carbon emissions on IPO underpricing. The sample includes 1,720 new issues that went public between January 2004 and December 2021, of which 298 IPOs are classified in the Disclosure Group. The dependent variable is underpricing. For the independent variables, the Disclosure_dummy in the regression (1) is an indicator equal to one if the IPO is in the Disclosure Group. In regressions (2) to (5), the interest of carbon emission variable includes Ln (level of scope 1), Ln (level of scope 2), Intensity of scope 1, and Intensity of scope 2. Variable definitions are provided in Appendix A. Standard errors are clustered at the industry and year levels, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = Underpricing				
	(1)	(2)	(3)	(4)	(5)
Disclosure_dummy	3.061				
	(1.16)				
Ln (level of scope 1)		-1.060			
		(-0.89)			
Ln (level of scope 2)			-1.021		
			(-0.74)		
Intensity of scope 1				-1.358	
				(-1.00)	
Intensity of scope 2					-15.416
					(-1.40)
Ln (Proceeds)	4.662 ***	6.739 ***	6.851 ***	5.460 **	5.787
	(6.08)	(2.64)	(2.63)	(2.29)	(2.41) **
Leverage	-3.209 *	1.800	1.931	0.854	0.810
	(-1.65)	(0.28)	(0.29)	(0.14)	(0.13)
Tangibility	-1.668	-25.787 *	-28.690 **	-26.226 *	-25.687 **
	(-0.23)	(-1.85)	(-2.24)	(-1.95)	(-2.12)
CAPEX	0.335	3.380	3.438	3.553	3.436
	(0.51)	(1.04)	(1.06)	(1.14)	(1.10)
R&D	-0.081	-0.532 **	-0.535 **	-0.521 **	-0.504 **
	(-1.41)	(-2.43)	(-2.48)	(-2.38)	(-2.28)
Fraction sold	-12.638	-14.605 *	-14.832 *	-14.963 *	-14.489
	(-1.59)	(-1.66)	(-1.67)	(-1.66)	(-1.64)
VC-backed	6.022 **	9.602	9.915	10.147	9.870
	(2.11)	(1.19)	(1.26)	(1.24)	(1.21)
PE-backed	-6.020	-11.770	-11.802	-12.566	-11.774
	(-1.56)	(-1.39)	(-1.35)	(-1.48)	(-1.40)
NYSE	-1.715	-2.442	-2.494	-2.751	-3.245
	(-0.58)	(-0.52)	(-0.54)	(-0.60)	(-0.73)
Underwriter reputation	-6.471	-12.696 *	-12.823 *	-12.812 *	-12.910 *
	(-1.49)	(-1.74)	(-1.76)	(-1.74)	(-1.77)
Auditor reputation	-0.872	6.975	6.831	6.449	7.001
	(-0.27)	(1.38)	(1.40)	(1.32)	(1.41)
ROA	2.410 ***	3.470	3.420	2.955	-0.072
	(2.64)	(0.89)	(0.87)	(0.86)	(-0.80)
Market momentum	2.999 ***	5.094 ***	5.105 ***	5.151 ***	5.200 ***
	(5.87)	(4.07)	(4.09)	(4.20)	(4.46)
Market volatility	3.719 *	3.871	3.808	3.849	4.285
	(1.66)	(0.56)	(0.56)	(0.57)	(0.65)
FF49 industry dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Number of observations	1,720	298	298	298	298
Adj-R^2	0.226	0.386	0.385	0.385	0.388

Table 8 The influences of carbon emissions on long-run abnormal returns

This table presents the regression results of carbon emissions on long-run post-IPO performance. The long-run performance is measured by one-, two-, and three-year post-IPO buy-and-hold abnormal returns, respectively. The sample includes 1,720 new issues that went public between January 2004 and December 2021, of which 298 IPOs are classified in the Disclosure Group. The dependent variable in Panel A is 1 year (250 days) buy-and-hold post-IPO abnormal return (BHAR250), in Panel B is 2 years (500 days) buy-and-hold post-IPO abnormal return (BHAR500), and in Panel C is 3 years (750 days) buy-and-hold post-IPO abnormal return (BHAR750). For the independent variables, the Disclosure_dummy in the regression (1) is an indicator equal to one if the IPO is in the Disclosure Group. In regressions (2) to (5), four carbon emission variables are used in the empirical analyses: total carbon scope 1, scope 2, and the intensities of carbon scope 1 and scope 2 emission, respectively. Variable definitions are provided in Appendix A. Standard errors are clustered at the industry and year levels, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% levels, respectively.

Panel A: Regression of BHAR250

	Dependent variable = BHAR250				
Independent variables	(1)	(2)	(3)	(4)	(5)
Disclosure_dummy	0.177***				
	(3.74)				
Ln (level of scope 1)		0.084***			
		(3.48)			
Ln (level of scope 2)			0.105**		
			(3.76)		
Intensity of scope 1				0.054	
				(1.13)	
Intensity of scope 2					0.346*
					(1.67)
Ln (Proceeds)	-0.44**	-0.122***	-0.163**	-0.023	-0.031
	(-2.28)	(-2.77)	(-3.35)	(-0.59)	(-0.83)
Leverage	-0.052	-0.096	-0.122	-0.037	-0.043
	(-1.55)	(-0.86)	(-1.13)	(-0.30)	(-0.36)
Tangibility	0.156*	-0.134	0.059	0.052	0.111
	(1.90)	(-0.59)	(0.28)	(0.21)	(0.53)
CAPEX	-0.014*	0.020	0.021	0.003	0.003
	(-1.78)	(1.12)	(1.20)	(0.16)	(0.18)
R&D	-0.000	-0.004*	-0.004*	-0.004*	-0.005*
	(-0.08)	(-1.87)	(-1.70)	(-1.77)	(-1.84)
Fraction sold	0.173**	0.286*	0.299*	0.313*	0.305*
	(2.05)	(1.87)	(1.95)	(1.97)	(1.91)
VC-backed	0.028	0.150	0.141	0.093	0.092
	(0.50)	(1.20)	(1.15)	(0.70)	(0.70)
PE-backed	0.127**	0.081	0.069	0.136	0.117
	(2.36)	(0.71)	(0.62)	(1.17)	(1.00)
NYSE	-0.027	-0.150	-0.153	-0.126	-0.114
	(-0.72)	(-1.65)	(-1.61)	(-1.37)	(-1.25)
Underwriter reputation	0.106**	0.333**	0.337**	0.350**	0.358**
	(2.16)	(2.30)	(2.34)	(2.34)	(2.38)
Auditor reputation	0.065	-0.112	-0.115	-0.061	-0.070
	(1.41)	(-0.82)	(-0.83)	(-0.43)	(-0.50)
ROA	0.042***	0.004	-0.002	0.044	0.054
	(2.66)	(0.06)	(-0.03)	(0.40)	(0.52)
Market momentum	-4.324***	-3.226*	-3.151*	-3.665**	-3.847**
	(-4.53)	(-1.83)	(-1.83)	(-2.18)	(-2.27)
Market Volatility	-2.885	-17.472*	-17.078*	-16.908*	-17.770*

	(-0.70)	(-1.91)	(-1.91)	(-1.88)	(-1.93)
Underpricing	-0.066	-0.082	-0.084	-0.097	-0.088
	(-1.04)	(-0.78)	(-0.82)	(-0.93)	(-0.83)
FF49 industry dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Number of observations	1,720	298	298	298	298
Adj-R^2	0.070	0.084	0.091	0.043	0.047

Panel B: Regression of BHAR500

	Dependent variable = BHAR500				
Independent variables	(1)	(2)	(3)	(5)	(6)
Disclosure_dummy	0.271 ***				
	(3.53)				
Ln (level of scope 1)		0.104 ***			
		(3.15)			
Ln (level of scope 2)			0.133 **		
			(3.79)		
Intensity of scope 1				0.035	
				(0.55)	
Intensity of scope 2					0.369
					(1.26)
Control variables	Yes	Yes	Yes	Yes	Yes
FF49 industry dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Number of observations	1,720	298	298	298	298
Adj-R^2	0.057	0.104	0.109	0.080	0.083

Panel C: Regression of BHAR750

	Dependent variable = BHAR750				
Independent variables	(1)	(2)	(3)	(5)	(6)
Disclosure_dummy	0.414 ***				
	(3.56)				
Ln (level of scope 1)		0.204 ***			
		(3.81)			
Ln (level of scope 2)			0.248 **		
			(4.00)		
Intensity of scope 1				0.161	
				(1.53)	
Intensity of scope 2					0.438
					(0.89)
Control variables	Yes	Yes	Yes	Yes	Yes
FF49 industry dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Number of observations	1,720	298	298	298	298
Adj-R^2	0.045	0.122	0.126	0.081	0.076

Table 9 Correction for sample selection bias: Heckman two-stage approach

This table presents the results of the Heckman two-stage sample selection model. The sample includes 1,720 new issues that went public between January 2004 and December 2021, of which 298 IPOs are classified in the Disclosure Group. Panel A reports the result for the first stage, which is a probit model describing the probability of the IPO being classified in the Disclosure Group. The second stage least squares regressions estimate the impact of carbon emissions on IPO performance measures, including initial offer value (reported in Panel B), price-revision (Panel C), underpricing (Panel D), and BHAR250 (Panel E). Four carbon emission variables are used in the empirical analyses: total levels of carbon scope 1, scope 2, and the intensities of carbon scope 1 and scope 2 emission, respectively. Variable definitions are provided in Appendix A. Standard errors are clustered at the industry and year levels, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% levels, respectively.

Panel A: 1st stage: Probit model

Independent variables	1st stage Prob(Disclosure)
Ln_sales	0.236 *** (8.60)
Leverage	-0.124 (-1.31)
Tangibility	-0.094 (-0.48)
CAPEX	0.032 (1.46)
R&D	0.006 ** (2.07)
VC-backed	0.136 (1.13)
PE-backed	-0.220 * (-1.81)
NYSE	0.106 (1.18)
Underwriter reputation	0.192 (1.45)
Auditor reputation	-0.064 (-0.56)
ROA	-0.057 (-0.98)
Number of observations	1,720
LR χ^2	149.58
(p-value)	(0.00)

Panel B: 2nd stage regression of initial offer value

	2nd stage			
	Dependent variable = Initial offer value			
Independent variables	(1)	(2)	(3)	(4)
Ln (level of scope 1)	-0.142 ** (-2.49)			
Ln (level of scope 2)		-0.146 ** (-2.12)		
Intensity of scope 1			-0.111 * (-1.74)	
Intensity of scope 2				-0.913 * (-1.92)

Control Variables	Yes	Yes	Yes	Yes
Lambda (Inverse Mills' Ratio)	0.988 ***	0.979 ***	1.006 ***	1.048 ***
	(5.70)	(5.48)	(5.68)	(6.01)
FF49 industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
P-value of LR Test of Indep. Eq.(ρ=0)	<0.001 ***	<0.001 ***	<0.001 ***	<0.001 ***
Number of observations	298	298	298	298
Adj-R^2	0.824	0.822	0.818	0.820

Panel C: 2nd stage regression of price revision

	2nd stage			
	Dependent variable = Price revision			
Independent variables	(1)	(2)	(3)	(4)
Ln (level of scope 1)	-2.289 **			
	(-5.50)			
Ln (level of scope 2)		-2.964 **		
		(-5.73)		
Intensity of scope 1			-1.102	
			(-1.47)	
Intensity of scope 2				-9.247 **
				(-2.26)
Control Variables	Yes	Yes	Yes	Yes
Lambda (Inverse Mills' Ratio)	-6.599 ***	-6.789 ***	-6.408 ***	-5.984 ***
	(-2.88)	(-2.97)	(-2.85)	(-2.69)
FF49 industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
P-value of LR Test of Indep. Eq.(ρ=0)	0.214	0.133	0.995	0.984
Number of observations	298	298	298	298
Adj-R^2	0.172	0.191	0.084	0.095

Panel D: 2nd stage regression of underpricing

	Dependent variable = Underpricing			
Independent variables	(1)	(2)	(3)	(4)
Ln (level of scope 1)	-1.061			
	(-0.89)			
Ln (level of scope 2)		-1.021		
		(-0.74)		
Intensity of scope 1			-1.369	
			(-1.04)	
Intensity of scope 2				-15.808
				(-1.41)
Control Variables	Yes	Yes	Yes	Yes
Lambda (Inverse Mills' Ratio)	0.254	0.196	0.399	1.274
	(0.05)	(0.04)	(0.08)	(0.24)
FF49 industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
P-value of LR Test of Indep. Eq.(ρ=0)	0.854	0.843	0.713	0.680
Number of observations	298	298	298	298
Adj-R^2	0.384	0.383	0.383	0.386

Panel E: 2nd stage regression of long-run performance

Independent variables	2nd stage Dependent variable = BHAR250 (1)	(2)	(3)	(4)
Ln (level of scope 1)	0.083 ***			
	(3.45)			
Ln (level of scope 2)		0.105 ***		
		(3.71)		
Intensity of scope 1			0.048	
			(1.07)	
Intensity of scope 2				0.284
				(1.40)
Control Variables	Yes	Yes		
Lambda (Inverse Mills' Ratio)	0.216 **	0.221 **	0.213 *	0.200 *
	(2.03)	(2.09)	(1.87)	(1.77)
FF49 industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
P-value of LR Test of Indep. Eq.(ρ=0)	0.175	0.131	0.577	0.604
Number of observations	298	298	298	298
Adj-R^2	0.095	0.103	0.054	0.056

Table 10 Correction for Sample Selection Bias: Entropy Balance Estimation

This table presents the analysis performed regressions with an entropy-balanced sample. For each of the regressions of initial offer value (Table 4), price revision (Table 5), underpricing (Table 6), and long-run performance (Table 7), we reweight the other IPO sample (non-carbon emissions) such that there are no statistically significant differences between the treatment group (carbon emission IPOs) and control group (non-carbon emission IPOs) for all control variables (all independent variables except carbon emission variables) at the first and second moments (Hainmueller, 2012). The dependent variable in Panel A is initial offer value, in Panel B is price revision, in Panel C is underpricing, and is long-run post-IPO performance in Panel D. Variable definitions are provided in Appendix A. P-values are reported in parentheses. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% levels, respectively.

Panel A: Initial offer value

	Dependent variable = Initial offer value			
Carbon related variable =	Level of scope 1	Level of scope 2	Intensity of scope 1	Intensity of scope 2
Coefficient on Carbon related variable	-0.022**	-0.020*	-0.068	-0.359
(t-statistic)	(-2.01)	(-1.71)	(-1.11)	(-1.34)
Control Variables in Table 4	Yes	Yes	Yes	Yes
FF49 industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Number of observations	1,720	1,720	1,720	1,720
R^2	0.852	0.852	0.852	0.852

Panel B: Price revision

	Dependent variable = Price revision			
Carbon related variable =	Level of scope 1	Level of scope 2	Intensity of scope 1	Intensity of scope 2
Coefficient on Carbon related variable	-0.262**	-0.264**	-0.720	-6.636**
(t-statistic)	(-2.51)	(-2.54)	(-1.09)	(-2.39)
Control Variables in Table 4	Yes	Yes	Yes	Yes
FF49 industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Number of observations	1,720	1,720	1,720	1,720
R^2	0.262	0.262	0.257	0.261

Panel C: Underpricing

	Dependent variable = Underpricing			
Carbon related variable =	Level of scope 1	Level of scope 2	Intensity of scope 1	Intensity of scope 2
Coefficient on Carbon related variable	-0.144	-0.106	-2.585	-16.461*
(t-statistic)	(-0.43)	(-0.31)	(-1.10)	(-1.80)
Control Variables in Table 4	Yes	Yes	Yes	Yes
FF49 industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Number of observations	1,720	1,720	1,720	1,720
R^2	0.403	0.403	0.404	0.405

Panel D: Long-run performance

	Dependent variable = BHAR250			
Carbon related variable =	Level of scope 1	Level of scope 2	Intensity of scope 1	Intensity of scope 2
Coefficient on Carbon related variable	0.022 ***	0.021 ***	0.087 **	0.416 **
(t-statistic)	(4.20)	(4.10)	(2.20)	(2.50)
Control Variables in Table 4	Yes	Yes	Yes	Yes
FF49 industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Number of observations	1,720	1,720	1,720	1,720
R^2	0.234	0.233	0.224	0.226

Table 11 Calendar-time Portfolio Regression

This table presents the calendar-time portfolio regression results. The sample includes 1,720 new issues that went public between January 2004 and December 2021, of which 298 IPOs are classified in the Disclosure Group. Calendar-time portfolio includes two-year post-IPO monthly returns beginning from the close of the first IPO month. Four portfolios are constructed: Non-Disclosure, Port1, Port2, and Port3. Port1, Port2, and Port3 are the three portfolios classified by total level of scope 1 carbon emissions that are reported in Panel C of Table 3. RMRF, SMB, and HML are three Fama-French three factors' monthly returns. GMB is the green-minus-brown monthly return. We run the regression of excess return (portfolio return minus risk-free return) on the RMRF, SMB, HML, and GMB. T-statistics are reported in parentheses. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% levels, respectively.

	Non-Disclosure	Port 1 (Low carbon emission)	Port 2	Port 3 (High carbon emission)
Intercept	-0.377	0.619*	0.376	0.260
	(-1.54)	(1.73)	(0.69)	(0.57)
RMRF	1.008***	1.256***	0.954***	1.215***
	(16.37)	(14.10)	(6.93)	(10.82)
SMB	1.321***	1.144***	1.056***	0.877***
	(12.29)	(7.33)	(4.74)	(4.32)
HML	-0.466***	-0.528***	-0.274	-0.582***
	(-5.88)	(-4.62)	(-1.58)	(-4.02)
GMB	0.325*	0.228	0.130	-0.978***
	(1.78)	(0.86)	(0.31)	(-2.92)
Number of months	227	222	170	198
Adj-R^2	0.757	0.649	0.401	0.492

Appendix A. Variable Definitions

Variable	Definition
Panel A1: IPO Valuation and Aftermarket Performance	
Initial offer value	The midpoint of the initial price range (SDC) multiplied by the number of post-IPO common shares outstanding (Compustat item CSHOQ), divided by the first post-IPO book value of total assets (Compustat item ATQ). (Reference: Willenborg et al. (2015), p.1133-1136)
Price revision	The price change, in percentage, from the midpoint of the initial price range (from SDC) to the offer price (SDC) in IPO.
Final offer value	The IPO offer price (SDC) multiplied by the number of post-IPO shares outstanding (Compustat item CSHOQ), divided by the first post-IPO book value of total assets (Compustat item ATQ)
Underpricing	The price change, in percentage, from the offer price (from SDC) to the first-day closing price (CSRP item PRC).
BHAR250	One-year (250 days) buy-and-hold post-IPO abnormal returns from the first-day close. BHAR250 = $\prod_{t=2}^{251}(1+R_{i,t})-\prod_{t=2}^{251}(1+R_{m,t})$, where $R_{i,t}$ is the issuer's daily return (CRSP item RET), $R_{m,t}$ is the market return, which is proxied by CRSP value-weighted market portfolio return (CRSP item VWRETD).
BHAR500	Two-year (500 days) buy-and-hold post-IPO abnormal returns from the first-day close.
BHAR750	Three-year (750 days) buy-and-hold post-IPO abnormal returns from the first-day close.
Panel A2: Carbon emission variables	
Level of scope 1	Total amount (tons CO_2e) of firm-level carbon emission in the source of scope 1 (Trucost item di_319413).
Level of scope 2	Total amount (tons CO_2e) of firm-level carbon emission in the source of scope 2 (Trucost item (di_319414)).
Intensity of scope 1	GHG Intensity scope 1 (Trucost item di_319407)
Intensity of scope 2	GHG Intensity scope 2 (Trucost item di_319408)
Panel A3: Deal and Firm Characteristics	
Proceeds	The total proceeds from the IPO in millions of US dollars. (SDC)
VC-backed	The dummy variable equals one if the IPO is backed by venture capital and zero otherwise. (SDC)
PE-backed	The dummy variable equals one if the IPO is backed by private equity and zero otherwise. (SDC)
Underwriter reputation	The dummy variable equals one if the lead underwriter of the IPO has an updated Carter and Manaster (1990) rank of eight or more and zero otherwise. (SDC)
Auditor reputation	The dummy variable equals one if the auditor of the IPO is one of the big four accounting firms.

Fraction sold	The fraction sold in the IPO. Fraction sold is calculated as the number of primary shares offered in the IPO (SDC) divided by the number of post-IPO shares outstanding (Compustat item CSHOQ).
NYSE	The dummy variable equals one if the IPO is listed on NYSE and zero otherwise. (SDC)
Market momentum	Pre-IPO market return. For each offering, a three-month (63 trading days) weighted market return before the IPO date is computed as a weighted average of the buy-and-hold returns of the CRSP value-weighted market index (CRSP item VWRETD). The weights are three for the most recent 21 trading days (-21 to -1), two for the next group of trading days (-42 to -22), and one for the earliest 21 trading days (-63 to -43) before the IPO date. We then divide this weighted sum by six to get a weighted market return;
Market volatility	Pre-IPO market return volatility, which is computed as the standard deviation of returns on the CRSP value-weighted market index (CRSP item VWRETD) over the 21 trading days (-21, -1) before the IPO date.
Assets	Pre-IPO book value of total assets. (Compustat item ATQ)
Sales	Pre-IPO annual firm sales, computed as the sales in the most recent four quarters before the IPO date. (Compustat item SALEQ)
Leverage	Pre-IPO financial leverage, computed as total debt in current liabilities (Compustat item DLCQ) plus total long-term debt (Compustat item DLTTQ), divided by total assets (Compustat item ATQ). All are reported in the most recent balance sheet before the IPO.
Tangibility	Pre-IPO tangibility, computed as property, plant, and equipment (Compustat item PPENTQ) divided by total assets (Compustat item ATQ). All are reported in the most recent balance sheet before the IPO.
R&D	Pre-IPO annual R&D expenditures, computed as the research and development expenditures (Compustat item XRDQ) scaled by sales (Compustat item SALEQ). Both are reported in the most recent four quarters before the IPO date.
ROA	Pre-IPO return on assets, computed as annual net income (Compustat item NIQ) in the most recent four quarters before the IPO date, scaled by average total assets (Compustat item ATQ) before the IPO date.
CAPEX	Pre-IPO capital expenditures, computed as capital expenditures (Compustat item CAPX) scaled by sales (Compustat item SALEQ) in the most recent four quarters before the IPO date.
Panel A4: Climate risk measures	
MCCC_shock	MCCC_shock is a measure of shocks to climate concerns. Ardia et al. (2021) construct the Media Climate Change Concerns Index (MCCC index) using data from eight major U.S. newspapers. Following Ardia et al. (2021), we estimate an AR(1) model using the 36 months of the MCCC index data ending in month t-1. The MCCC_shock is the prediction error to month t's realization of MCCC minus the AR(1) model's prediction.
Dummy_Paris	The dummy variable equals one if the IPO went public after the Paris Agreement (December 2015)