Are Sell-Side Analysts Up to the Challenge of Climate Change?

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Abstract

Estimating the financial implications of climate change presents a significant challenge, one that aligns with the specialized expertise of sell-side analysts. This study examines analysts' performance in this context and finds that they exhibit systematic pessimism in their earnings forecasts for carbon-intensive firms. Our results suggest this pessimism is more likely represents a mistake rather than deliberate strategic behavior. Analysts appear to conflate elevated discount rates with diminished earnings prospects. Analysts with prior professional experience in pollution-intensive industries exhibit greater pessimism, suggesting this error is more likely driven by limitations in financial expertise rather than a lack of industry-specific knowledge.

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1. Introduction

Climate change poses a novel and complex challenge to investors trying to evaluate polluting firms. This challenge requires projecting, at a minimum, the magnitude of climate change, the firm's exposure to climate shifts, the anticipated regulatory responses and their corporate implications, and the emergent technological solutions that could mitigate the detrimental effects of climate change. These complex interactions between the scientific, political, and technological considerations, often collectively referred to as "transition risk" (e.g., Bolton and Kacperczyk, 2023), generate a degree of difficulty rarely seen in investment history.

Given their highly specialized expertise, sell-side analysts should be among the most well-informed regarding the likely effects of climate change at the individual firm level, yet the literature has largely found that analysts are not up to the challenge.[1] Specifically, the literature has demonstrated that climate change tends to induce analyst pessimism. For example, Dong, Fisman, Wang and Xu (2021) document a negative relation between air pollution on the day of an analyst's corporate site visit and the analyst's subsequent earnings forecast for that firm. Cuculiza, Kumar, Xin and Zhang (2021) show that analysts in states where firms have higher sensitivity to abnormal temperature changes issue relatively more pessimistic forecasts in periods following large temperature increases. Khanchel, Rjiba and Hussain (2023) find that analysts issue less favorable recommendations for firms with higher exposure to climate change. While the literature in this area all point in the same direction, the underlying mechanism is unclear.

In this paper, we further investigate the relationship between climate change and analysts' pessimism, as well as its underlying causes. Our specific focus is a firm's transition risk, which

[1] Additionally, several papers document that analysts are reluctant to address the issue of climate change. For example, Mburu and Bonaparte (2024) find that analysts tend to avoid covering firms with low ESG scores. Chan (2024) document that analysts tend not to include in their report climate change effect.

we proxy using carbon emissions. We find that analysts exhibit greater pessimism toward high-emission firms relative to other firms, a phenomenon we term "brown-firm pessimism", or BFP. Our central hypothesis is that due to the relative novelty of climate change as a priced factor, analysts conflate its impact on cash flows with its effect on discount rates. We find robust empirical support for this hypothesis: analysts' BFP occurs primarily during periods when a brown firm experiences an increase in its discount rate. Importantly, this mechanism should apply only to brown firms, and indeed, we find no evidence of a similar pattern affecting non-polluting firms.

We investigate additional potential explanations for BFP. We ask whether BFP is strategic, whereby a brown-firm analyst deliberately issues lower forecasts because doing so either matches the political tilt of their employer or otherwise accrues benefits to the analyst's career. Our results indicate no significant association between BFP and the political contributions of their employers, nor between BFP and the analyst's subsequent career outcomes. To the contrary, we find that lower-quality analysts, as proxied by their Institutional Investor All-American star status and their tenures as analysts, exhibit higher BFP, consistent with the notion that such pessimism stems from an error. When we test for the possibility that a lack of brown-industry knowledge drives BFP, we instead find the opposite: exposure to brown-industry information is associated with *increased* pessimism. For instance, analysts with prior work experience in brown industries tend to exhibit higher BFP than other analysts.

Empirically, our primary dependent variable is an analyst's annual earnings per share (EPS) forecast error, and the key independent variable is a firm's carbon emissions, which following Ilhan et al. (2021) and Bolton and Kacperczyk (2021) we measure emissions at the industry level. We begin with a preliminary test to see if emissions are negatively correlated with its analysts' forecasts errors, as might be expected given the existing literature on climate change and analysts.

Our baseline results establish confirm this prior: the browner the industry of the firm is, the more pessimistic the earnings forecasts. We highlight here that this brown-firm pessimism is based on a forecast horizon of one year, meaning the pessimism does not reflect the arduous challenge of estimating a firm's complete transition risk profile, but only the more compact task of estimating its immediate-term implications.

Having confirmed a link between a firm's "brownness" and analysts' forecast pessimism, we investigate whether this link represents an intentional strategy by the analysts. We undertake three lines of analysis here. The first is based on the supposition that BFP is a deliberate attempt to align the analyst's forecast to the political ideology of their brokerage. We categorize the brokerage house's political orientation by its political action committee contributions. When we test whether BFP is correlated with the brokerage house's politics, we find no relation, suggesting that BFP is not driven by analysts who deliberately understate earnings forecasts for polluting firms to curry favor with their left-leaning employers. The second line investigates whether analysts' career concerns drive BFP. The supposition here is that by issuing deliberately understated earnings forecasts for brown firms, analysts accrue personal benefits, career-wise. We test whether analysts' BFP is correlated with three career outcome variables: 1) being voted as an Institutional Investor All-American ("all-star") analyst; 2) exiting the IBES database; and 3) moving up to a large brokerage house. For all three cases, we find no significant evidence that BFP is correlated with career outcomes. The third line we investigate is whether BFP is less likely when the issuing analyst is more skilled. For these tests, we flip the supposition: if BFP is not strategic but rather a mistake, it should be smaller in magnitude for higher-quality analysts. We follow Andrade et al. (2013) and proxy for an analyst's skill level in two ways: the analyst's star status

and their tenure as an analyst.[2] Our results show that BFP is lower both for star analysts and for more experienced analysts, consistent with the notion that BFP is not strategic but rather a mistake by less skilled analysts.

If brown-firm pessimism is a mistake, a natural question to ask is what the nature of the mistake is. We posit a novel hypothesis: When brown firms suffer from negative news, some analysts confuse an increase in the discount factor with a decrease in earnings. Put in terms of the standard valuation formula, analysts mistake an increase in the denominator for a decrease in the numerator, what we term "Denominator to Numerator Confusion", or DNC. Whereas traditional risk factors (e.g., market beta and book-to-market) have been known for decades, climate change has only recently been discussed as a risk factor (e.g., Engle et al., 2020), leaving open the possibility that analysts did not properly account for it. According to the hypothesis, when analysts observe negative news about brown firms but no change in the traditional risk factors, they confuse an increase in the discount factor with a decrease in earnings.

We measure changes in the discount factor using the annual change in a composite cost of capital estimate for each firm, calculated using four established methods from the literature. When we regress forecast errors on the interaction of Scope 1 emissions and changes in the discount rate, we find that for brown firms only, analysts tend to be more pessimistic when the firm's discount rate increases, consistent with our DNC hypothesis. We then conduct two additional tests of the hypothesis. First, we proxy for a firm's receiving bad news with *Low Stock Return,* an indicator for firms in the bottom decile of the previous year's returns, and find that analysts' pessimism toward brown firms is significantly greater for such firms. Second, following Engle et al. (2020),

[2] Using all-star status follows from the literature demonstrating that all-star analysts are more skilled than their non-star peers (e.g., Stickel, 1992; Leone and Wu, 2007; Fang and Yasuda, 2014; Aharoni et al, 2024). Using tenure (Mikhail, Walther, and Willis, 1997) is based on the dual assumptions that a longer-tenured analyst 1) has more accrued human capital and 2) has demonstrated their competence by having survived as an analyst for a longer period of time.

we use the *Wall Street Journal* Climate Change News Index to capture periods of heightened climate-change attention and associated regulatory risk. The results indicate that BFP is higher when this index is high. Collectively, the test results strongly support the DNC hypothesis that brown firm analysts confuse an increase in the discount rate with a decrease in expected cash flows.

Our earlier finding that quality analysts do not exhibit BFP is consistent with the DNC hypothesis – i.e., quality analysts do not make the DNC climate-finance error – but also hints to another intuitive possibility: Quality analysts may have an informational advantage, one which leads them to be less pessimistic. Our final tests investigate whether BFP is diminished for analysts with exposure to brown-industry information. We use three proxies for exposure: 1) whether analysts had work experience in brown firms before becoming analysts; 2) the number of brown firms in their portfolio in the recent year; and 3) the average environmental risk score of the firms in their portfolio. We find that, rather counterintuitively, for all three proxies, greater exposure to brown firms exacerbates BFP rather than attenuates it. This suggests that analyst skill, rather than increased exposure to brown-firm information, is more important in mitigating BFP. We propose that the observed increase in pessimism may be driven by a generally more negative outlook on environmental measures within brown industries. Analysts with greater exposure to these industries, such as those who previously worked in them, may be more likely to internalize these views, leading to heightened pessimism in their forecasts. The more exposure to brown-industry information, the more pessimistic the analyst is about brown firms. The aggregate results suggest that analyst skill, as opposed to their exposure to brown-firm information, is more important for reducing BFP.

Our paper makes several contributions. First, we add to the literature on analysts and climate change. Several papers document that analysts struggle to properly incorporate the effect

of climate change into their research output. Mburu and Bonaparte (2024) report that firms from brown industries have less analyst coverage and less accurate earnings forecasts. Zhang and Kanagaretnam (2024) document a decline in forecast accuracy following climate disasters, particularly in brown industries. Chan (2024) find that only 11% of all analysts include climate change in their reports. Several papers document that local events influence analysts in their predictions. Factors such as exposure to severe weather (Pankratz, Bauer, and Derwall, 2023), days with higher pollution during site visits (Dong, Fisman, Wang and Xu, 2021) and personal experience with climate disasters (Han, Mao, Tan and Chang, 2023) lead to analysts' pessimism about polluting firms. Our paper adds to this literature, first by showing systematic pessimism in predicting the earnings of firms in brown industries, and then, more importantly, by showing that this pessimism is concentrated among firms that experience an increase in their cost of equity. We argue that this systematic mistake stems from the inability of some analysts to distinguish between an increased risk and a decrease in profitability resulting from climate change.

Our second contribution concerns the effect of information on the adoption of climate change policies. Some research (e.g., Luís, Vauclair, and Lima, 2018; Halady and Rao, 2010) argue that an obstacle to adopting more aggressive climate change policies is the lack of information about the potential costs of climate change if preventative measures are not adopted. Others argue that more information can lead to the opposite effect, as people, especially the young, feel overwhelmed and overestimate the severity of the problem.[3] Our findings that arguably one of the most knowledgeable groups of individuals of brown firms–financial analysts with previous work experience in brown industries–are also the most pessimistic suggests that even top professionals are susceptible to overestimating the severity of the (short-term) problem.

[3] See, for example Bawden and Robinson (2009) for information overload.

Our third contribution is related to heterogeneity in analysts' abilities. Numerous papers try to determine whether those analysts who are selected to be stars have better abilities than their non-star counterparts. For example, Emery and Li (2009) argue that star status largely represents a popularity contest, while Leone and Wu (2007) and Fang and Yasuda (2014) argue that star status reflects analysts' skills. Our paper presents compelling evidence in favor of the latter argument, that I/I rankings are based on merit. Climate change is a relatively new and complicated phenomenon with little theoretical understanding that analysts need to research. Our findings indicate that while non-star analysts appear to be confused by the novel challenge of climate change – i.e., they suffer from DNC – stars are not, managing to forecast earnings for brown firms similarly to non-brown firms.

The remainder of this paper is organized as follows. In Section 2, we outline the sample construction. In Section 3, we investigate whether analysts' forecasts for brown firms are comparable to those for all other firms. In Section 4, we test for denominator to numerator confusion. Section 5 investigates whether exposure to information improves brown-firm pessimism. Section 6 concludes.

2. Sample Construction

Our primary unit of observation is an analyst's signed *Forecast Error*, defined as the difference between the realized annual earnings per share (EPS) and the earliest annual EPS forecast made by each analyst for each firm they cover, scaled by the price per share on the day prior to the forecast announcement. We extract annual earnings per share forecasts and other analyst-related information from the IBES detail files. For each analyst, we keep their initial annual earnings forecast for a company made at the start of the fiscal year. For each firm, we then use linking tables

provided by the WRDS to incorporate the COMPUSTAT and CRSP data to construct the firm-level variables. Each resulting observation represents an analyst-firm-year triplet.

To code a firm's "brownness", we obtain firm-level carbon and greenhouse gas emissions data from Trucost. The availability of carbon emission data limits the sample to the timespan between 2005 and 2019. Using the ISIN identifier, we first link Trucost data with Capital IQ data. Then we employ the CUSIP identifier to match the Trucost and IBES data. Our analysis focuses on Scope 1 emissions as reported by the Trucost, where "Scope 1 emissions" refer to the direct emissions originating from operations of subsidiaries or units owned or controlled by the company. To measure exposure to environmental risk at the firm level, we obtain the RepRisk Index from RepRisk and merge the index with our sample using the ISIN identifier.

Summary statistics are presented in Table 1. Detailed descriptions of variable constructions are included in the table caption as well as in the appendix.

[Table 1 about here]

3. Are analysts' forecasts for brown firms biased relative to non-brown firms?

3.1 Baseline tests

Our first goal is to establish whether cross-sectional variation in analyst forecasts conditional on the firm's brownness exists. Is the intensity of a firm's carbon emissions associated with its analysts' forecast errors?

We use two measures of emissions, both based on firms' Scope 1 emissions. The first measure is at the firm's industry level: total Scope 1 carbon emissions of firms in the same industry divided by the total revenue of firms in the same industry. This follow Ilhan et al. (2021) and Bolton and Kacperczyk (2021), both of whom argue that industry-level pollution is a superior proxy for a firm's emissions than their individually-reported levels. The second measure is the

firm's Residual Scope 1 emissions, defined as the residual from regressing Scope 1 emissions of the firm on Scope 1 emissions of the industry, where Scope 1 emissions of the firm are calculated as the natural logarithm of firm Scope 1 carbon emissions, divided by revenue at the firm level. This residual represents the firm-level deviation from an expected level of emissions, given the industry in which the firm operates.

For analyst *i* covering firm *j* at time *t*, we run OLS regressions of the following form:

$$FE_{i,j,t} = a + bScope1Industry_{j,t} + c\ Emissions_{i,j,t} + d\ Controls_{i,j,t} \qquad (1)$$

where *FE* is the analyst's forecast error for the firm and *Controls* consists of both analyst- and firm-specific control variables.

In Model 1 of Table 2, we regress forecast errors on the firm's industry-level Scope 1 emissions. The results indicate that a firm's Scope 1 industry emissions negatively correlate with forecast errors. Given our definition of forecast errors, the negative coefficient implies that the "browner" the firm's industry is, the more pessimistic the forecasts of that firm's analysts are. In Model 2, we additionally control for analyst and firm characteristics, and the result remains: forecasts for brown firms are relatively more pessimistic.

[Table 2 about here]

To determine what incremental effect the firm's direct emissions might play, in Model 3 we regress forecast errors against the firm's residual Scope 1 emissions and observe that the coefficient on the firm-level emissions is not statistically significant. In Model 4, when we include both firm- and industry-level emissions as explanatory variables, only the industry-level measure is significant. That only industry-level pollution is associated with analyst pessimism points to the possibility that analysts' concerns with pollution are primarily with regulation, which is generally enacted at an industry, not firm, level.

3.2 Is BFP Strategic?

A possible explanation for BFP is that it is intentional by analysts. Prior literature has documented that analysts bias their results in response to their brokerage needs or their own career concerns. For example, Michaely and Womack (1999) find that analysts are too optimistic about firms that have investment relations with their brokerage house. Mola and Guidolin (2009) find that analysts are optimistic about firms that are held by mutual funds that are doing their business with their brokerage house. Mehran and Stulz (1985) argue that analysts over issue recommendations to encourage trade. Such papers raise the question of whether BFP represents strategic behavior by the participating analysts.

We run three sets of tests to determine whether BFP is strategic or, alternatively, a mistake. First, we examine whether the brokerage's political affiliation is correlated with BFP. Second, we test whether analysts' derive career benefits from BFP. Finally, we test whether BFP varies across analysts' skill levels.

3.2.1 Political Affiliation

The link between beliefs about climate change and political affiliation is well established, especially in the US. Palm et al. (2017) argue that Americans change their view about climate change according to their political affiliation and ideology. Luo and Zhao (2019) conduct an eye-tracking experiment demonstrating how political views inform individuals' focus when presented with a time-series graph of global temperatures. Similar observations have been documented in financial settings, with the literature documenting that political views affect the investment decisions of firms and individuals (e.g., Addoum and Kumar, 2016; Meeuwis et al., 2022; Hong

and Kostovetsky, 2012; Hutton et al, 2014). For political affiliations of analysts specifically, Jiang, Kumar, and Law (2016) find that Republican-leaning analysts tend to be more conservative (i.e., less bold) in their forecasts and to produce better-quality research. Kempf and Tsoutsoura (2023) find that credit rating analysts tend to downgrade firms more frequently if the analyst is registered in the party that is not in power.

Given this literature, a natural question is whether politics drives BFP. For example, analysts at left-leaning brokerage could "punish" brown firms in their earnings forecasts, either because their personal politics align with the brokerage or they aim to be consistent with their employer's ideology.

Before any formal analysis, however, we note that there are reasons to be skeptical of a political explanation. Our focus on one-year earnings forecasts, rather than prices, limits the scope of the climate change debate to at most 12 months into the future rather than decades. In the interval between the forecast announcement and the end of the fiscal year, it is unlikely that the firms' earnings will be affected by a catastrophic weather event. The short-term effects of climate change should be related to new legislation and pressure from public opinion. Crucially, these effects are unrelated to one's belief about the validity of climate change arguments. For example, even if the analyst is a die-hard Democrat, they may still believe that imposing climate change policies will not significantly hurt the short-term earnings of brown firms. Consistent with this observation, Addoum et al, 2023 find no relation between analysts' political affiliation and forecast changes after extreme temperature shocks.

To investigate whether BFP is (partly) driven by political affiliation, we obtain the contributions of PACs that represent the brokerage house from the OpenSecrets database. Additionally, we extract employees' contributions to political campaigns from the FEC database

and aggregate them into the brokerage house level to measure the political preferences of the brokerage firm. We then generate two firm-level measures of political affiliation. *Pro-Republican brokerage I* is a dummy variable that equals 1 if the *employees* of a brokerage house primarily donate to the Republicans. *Pro-Republican brokerage II* is a dummy variable that equals 1 if the *PACs* of a brokerage house primarily donate to the Republicans. Finally, we regress the forecast errors on an interaction variable of *scope 1 (industry)* and the political affiliation dummy variable.

The results, presented in Table 3, do not suggest that BFP is driven by political affiliation. The estimate of interest is the coefficient on the interaction term, which is not statistically significant for either measure of political affiliation. The coefficient on emissions alone notably remains negative and significant even after controlling for political affiliation. While the results do not preclude the possibility that analyst-level political affiliation drives brown-firm pessimism, at the brokerage level political affiliation is not significantly correlated with analysts' brown-firm pessimism.[4]

[Table 3 about here]

3.2.2 Career Concerns

Career concerns could potentially explain BFP. A literature documents analysts seemingly purposefully deviating from forecaster minimization in a manner that serves their employer's wider needs and, in turn, their own personal career concerns. For example, Baik and Yi (2006) posit that analysts may intentionally produce low earnings forecasts to curry favor for their investment banking division with the covered firm, an act which may serve analysts' and their employers' interests at the

[4] We also examine the direct political contributions of analysts. However, we can identify only a small number of analysts that contribute during our sample period. Our results do not indicate a relation between these contribution and brown-firm pessimism.

expense of their clients. Given this, BFP could be an artifact of a strategy by analysts to advance their careers.

We investigate this possibility by identifying three career-advancement outcomes and testing whether BFP is correlated with that outcome. The first outcome is an analyst's inclusion on Institutional Investor magazine's annual All-American ("all-star") analysts list. Being named on the list have been documented to bring considerable benefits in remuneration, access, and status (Groysberg, Healy, and Maber, 2011; Leone and Wu, 2007; Bradshaw, 2011; Soltes, 2014; Groysberg and Healy 2013; Rees et al. 2015). We use two metrics here. One corresponds to an analyst being ranked the top analyst in any All-American category, and the other corresponds to an analyst being ranked in the top four of any category.

The second career-advancement outcome is an analyst departing from the IBES database. Analysts may cease to be analysts for at least two major reasons: One is that they are dismissed for being incompetent, and the other is that they are promoted to, say, the buy side for being very competent. To isolate the former group, we limit the sample to analysts whose *General experience* is below the sample median. The operating assumption is that if one of these relatively junior analysts departs from the IBES database, it is likely a dismissal, not a promotion.

The final career advancement outcome is an analyst moving to a larger brokerage house. We identify whether an analyst has moved from a smaller firm to a larger one. We interpret such a change as an upward career move given the ostensibly larger remuneration and larger resources available at the larger firm.

We estimate the following logit model:

$$\Pr\left(Career_{i,t+1} = 1\right) = a + b\, X_{i,t} \qquad (2)$$

where $Career_{i,t+1}$ is the career-advancement outcome variable for analyst *i* in year *t+1* and $X_{i,t}$ is a vector of that analyst's characteristics in year *t*. The characteristic of interest is *Pessimism about "brown" industry*, the average of indicator variables, each of which equals 1 if *Forecast Error* is in the bottom quintile for a covered firm that belongs to a high-carbon intensity industry. We include several additional controls for the analyst's performance across their covered stocks during the year: *Pessimism*, the average of indicators, each of which equals 1 if *Forecast Error* is at the bottom quintile for a covered firm; "Brown" industry, the average of indicators, each of which equals 1 if a covered firm belongs to a high carbon intensity industry; and *Absolute Forecast Error*, the average of the absolute values of the analyst's forecast errors. Further, we include controls for the analyst's general experience (number of years in IBES), the size of their brokerage, the number of firms they followed, and the number of reports they issued in that year.

Table 4 tabulates the results from regressing each of the career outcome variables on the controls. The coefficient of interest, *Pessimism about brown firms*, is not statistically significant in any of the four models. That is, BFP does not confer a measured advantage in any of the four career outcomes we test. In Models 1 and 2, the negative and significant coefficient on *Absolute forecast error* suggests that, as arguably expected, accuracy across all firms, not just brown firms, is on average beneficial to analysts in terms of their future all-star status. In Model 3, the positive and significant coefficient on *Pessimism* indicates that extreme pessimism is associated with the analyst exiting their role as an analyst, but *Pessimism about brown firms* does not additionally alter that likelihood. That forecast pessimism is associated with losing one's position as an analyst suggests that BFP is likely to be unintended. The aggregated results across all four models suggest that analysts do not derive career benefits from being pessimistic about brown firms and consequently that BFP is unlikely to be driven by career concerns.

[Table 4 about here]

3.2.3 Analyst Quality

While the preceding tests in this section were premised on the hypothesis that BFP is strategic, we next consider the opposite possibility: that BFP is a mistake. Insofar as BFP is a mistake, we hypothesize that it should be less prevalent for higher-quality analysts.

We regress the analyst's forecast error against the firm's Scope 1 industry emissions which we additionally interact with the analyst's quality:

$$FE_{i,j,t} = a + b\ Scope1Industry_{j,t} + c\ Scope1Industry_{j,t} \times Quality_{i,j,t} + d\ Controls_{i,j,t} \quad (3)$$

A negative coefficient on *Scope1Industry* with a positive coefficient on the interaction term would indicate that BFP is attenuated for higher-quality analysts, consistent with the hypothesis that BFP is not strategic but rather a mistake made by lower-quality analysts.

We test for this using two separate proxies for an analyst's quality. Our first proxy of analyst competency is their Institutional Investor all-star status at the time of the forecast. The underlying assumption is that star analysts produce, on average, superior research compared to other analysts. The literature provides supportive evidence here, documenting (inter alia) that star analysts are more accurate forecasters (Stickel, 1992) and have stronger stock-picking skills (Desai et al., 2000; Leone and Wu, 2007). We acknowledge that some papers have challenged this characterization by reporting no relation between star status and their performance, as in Emery and Li (2009), but we note that star analysts not having "higher quality" should bias our tests from finding significant results.

Panel A of Table 5 presents the results from estimating Equation (3) using the two star-status indicator variables from Section 3.2.2: *Star analyst (top 1)* and *Star analyst (top 4)*. In Model 1, when we limit the "star" group to only those analysts selected for top ranking, the coefficient on *Scope1Industry* is negative (-0.0035), significant, and of the same magnitude as our previous tests. Importantly, and consistent with BFP being a mistake, we find that the coefficient on the interaction term between top-ranked analysts and *Scope1Industry* is positive (0.0023), significant, and about two-thirds in magnitude compared with the coefficient of *Scope 1* variable. That is, BFP is virtually non-existent for top-ranked analysts, consistent with the hypothesis that it is a mistake by lower-quality analysts. In Model 2, when we use the more traditional definition of star analysts – those that ranked in the top four of any Institutional Investor category – the coefficient on *Scope 1 (Industry)* remains negative (-0.0036), significant, and similar in magnitude to our prior estimates. The coefficient on the interaction term is again positive (0.0016) and significant, consistent with the hypothesis that BFP is a mistake. Notably, the diminution of the magnitude of the coefficient for the pool including lower-ranked star analysts in Model 2 versus only top-ranked star analysts in Model 1 suggests that BFP is decreasing in analyst quality, further consistent with the hypothesis that BFP is a mistake made by lower-quality analysts. We additionally observe that in both Models 1 and 2, the coefficient on star status alone is not statistically significant, ruling out the possibility that stars simply are less pessimistic about all firms, not just brown ones.

[Table 5 about here]

Our second proxy of analyst quality is their experience as an analyst. We calculate two separate measures of experience. The first is *General Experience*, equal to the natural logarithm of the number of months since an analyst first appeared in the IBES database. This metric corresponds to the analyst's overall experience as an analyst. The assumption here is that a longer-tenured analyst

has both accumulated more human capital and proven their competence by surviving in their role for a longer period. The second is *Firm Experience*, equal to the natural logarithm of the number of months since an analyst first covered a firm. This metric corresponds only to the analyst's experience covering the firm in question. The assumption here is slightly different: more experience covering a firm gives the analyst higher forecasting competency for that firm.

We use the two experience variables as proxies for analyst quality and again estimate Equation (3). In Panel B of Table 5, we find that analyst pessimism for brown firms is attenuated for either measure of analyst experience. For *General Experience,* the coefficient on *Scope 1 Industry* in Column 3 is negative, significant, and, at -0.0035, similar in magnitude to estimates in our prior models. The coefficient on the interaction term is 0.0009 and significant, implying that roughly surviving four years as an analyst yields sufficient human capital to undo BFP. The corresponding coefficients for Scope 1 Industry and the interaction term for *Firm Experience* in Column 4 are nearly identical in magnitude and significant, in this case implying that four years of experience covering a brown firm yields sufficient human capital to undo the analyst's BFP for that firm. Overall, the results for both experience measures are again consistent with the hypothesis that BFP is a mistake by lower-quality analysts. As analysts gain experience, they make fewer mistakes – in this case, they are less pessimistic – about brown firms.[5]

While the intuitive explanation of the cumulative results in this subsection is that higher-quality analysts are less susceptible to the BFP error, it may also be that experience and star status correlate with an unobservable variable (e.g., job security) that leads them to behave differently

[5] Given that the average forecast error (in Table 1) is positive, we note that BFP does not necessarily represent overall pessimism, whereby the forecast errors are on average negative, but rather pessimism relative to the non-brown firm baseline forecast error. The possibility then exists that BFP is coincident with lower absolute forecast errors, in which case BFP might be considered a positive attribute. This interpretation, however, requires that both 1) higher-quality analysts are worse at forecasting brown firms than their lower-quality peers and 2) brown firms are easier to predict, the joint possibility of which we consider less likely than the reverse.

than other analysts. One possibility is that the pessimism is deliberate and that our experience variables are correlated with some other unspecified incentive that makes experienced analysts less like to participate. While our findings fail to find a reason for analysts to intentionally bias their forecast, we acknowledge that we cannot categorically rule out all possible alternative explanations. That said, in the next section we attempt to identify a mechanism for BFP.

4. Cash Flows or Discount Rates?

The results from the preceding section indicate that analysts' pessimism about the short-term earnings is increasing in the "brownness" of firms and that this pessimism appears to be a mistake and not strategic. In this section, we propose and test a possible explanation for this mistake. We hypothesize that analysts of brown firms suffer from what we term "denominator to numerator confusion", or "DNC": analysts estimating the standard valuation equation ($P_0 = PV(Earnings)$) confuse an increase in the discount rate in the denominator with a decrease in the earnings in the numerator. Engle et al. (2020) suggest that brown firms are likely to have an additional risk factor related to exposure to climate change. This risk factor is relatively new to investors compared with traditional risk factors such as beta and book-to-market that have been known for decades, and firms in brown industries are likely to experience changes in their discount factor that are not experienced by firms in other industries. According to our DNC hypothesis, analysts who cover brown firms may be able to estimate that a firm's value is decreasing, but they confuse the increase in discount factor with a decrease in earnings.

We test for DNC by regressing the analyst's forecast error on the firm's Scope 1 industry emissions and their interaction with the (change in) discount rate proxy:

$$FE_{i,j,t} = a + b\ Scope1Industry_{j,t} + c\ Scope1Industry_{j,t} \times (\Delta)DiscountRate_{i,j,t} + d\ Controls_{i,j,t} \quad (4)$$

A negative coefficient on the interaction term would suggest that BFP is more severe when the (brown) firm's discount rate has increased, consistent with DNC hypothesis.

We test our DNC hypothesis using Δ*Cost of Capital,* the annual change in the average cost of capital estimates from the methods in Claus and Thomas (2001), Gebhardt, Lee and Swaminathan (2001), Easton (2004) and Ohlson and Juettner-Nauroth (2005).[6] We use this composite measure to reduce the possibility that our results are driven by any single cost-of-capital estimate. In Model (1) of Table 6, the coefficient on the interaction variable of *Scope1Industry* and Δ*Cost of Capital* is negative and significant, implying as brown firms' discount rates increase, BFP is more severe, consistent with the DNC hypothesis.[7] Notably, the coefficient on *Scope1Industry* alone is not significant, suggesting that BFP is specific to brown firms during periods when the climate change risk factor is high.

For robustness, we run two additional tests of the DNC hypothesis. The first is based on the following intuition: The hypothesis states that analysts can identify adverse information but may misattribute it, confusing a decline in expected earnings with an increase in the discount rate; consequently, this confusion should be most pronounced among firms receiving bad news. We proxy for bad news using a binary indicator, *Low Stock Return,* equal to 1 if the stock's previous annual return was in the lowest decile of all stock returns for that year, and examine whether these firms are more prone to exhibit BFP. In Model (2) of Table 6, the coefficient on the interaction term between *Scope1Industry* and *Low Stock Return* is negative and significant, consistent with the DNC hypothesis.

The second additional test is based on Engle et al. (2020), who argue that a high volume of climate change news is correlated with an increase in the risk of brown firms, as the likelihood of environmental regulation increases. The DNC hypothesis accordingly implies that during these periods,

[6] See Appendix A for detailed explanations of the four cost of equity capital measures.
[7] When we disaggregate Δ*Cost of Capital* into changes in its four constituent cost-of-capital measures and re-estimate our models with each measure, the coefficients on the interaction term are qualitatively similar, though not statistically significant.

analysts will be relatively more pessimistic about the earnings of brown firms. Our test will use *WSJ Climate Change News,* the average monthly *Wall Street Journal* Climate Change News Index over the past year. Unlike Δ*Cost of Capital* and *Low Stock Return*, however, *WSJ Climate Change News* is a single variable that applies to the entire cross section of firms at each point in time. In Model (3) of Table 6, the interaction term between *Scope1Industry* and *WSJ Climate Change Index* remains negative and significant, suggesting that when brown firms' discount rates have increased – which we assume occurs when the climate change index is high – analysts' BFP is exacerbated, consistent with the DNC hypothesis.

[Table 6 about here]

Cumulatively, the results in Table 6 support both the DNC proposition and, by extension, with the notion that BFP is a mistake rather than a deliberate strategy by analysts. One yet-undiscussed possibility is that unobserved characteristics associated with our analyst competence proxies explain BFP. However, the cross-sectional results using Δ*Cost of Capital* cast doubt on this. That analysts make mistakes only when covering firms that suffer an increase in their discount factor, compared to those that do not, diminishes the likelihood that analysts' characteristics drive BFP.

5. Exposure to Information

The results showing that higher-quality analysts (stars/experienced) exhibit less from BFP than other analysts (in Section 3.2.3) are consistent with the DNC hypothesis but additionally hint to the possibility that information, or lack thereof, drives BFP. If what we categorize as "quality" analysts simply have an informational advantage over other analysts, exposure to transition-risk information should attenuate BFP. Indeed, a standard assumption in economics is that more information should yield better predictions. In the climate change literature, some have proposed that awareness of climate change and specifically of its future costs is crucial to enacting the

necessary preventative measures (e.g., Luís, Vauclair, and Lima, 2018; Halady and Rao, 2010). That said, if quality analysts don't have an informational advantage but instead have a *skill* advantage, their observed superiority with regard to BFP would suggest they have superior processing of the same information sets as their lower-quality peers.

In this section, we investigate whether exposure to transition-risk information reduces BFP. Our tests entail regressing the analyst's forecast error on the firm's Scope 1 industry emission and its interaction with the analyst's exposure to transition-risk information:

$$FE_{i,j,t} = a + b\ Scope1Industry_{j,t} + c\ Scope1Industry_{j,t} \times Exposure_{i,j,t} + d\ Controls_{i,j,t} \quad (5)$$

A negative coefficient on *Scope1Industry* coupled with a positive coefficient on the interaction term would suggest that more exposure to relevant information improves forecasts of brown firms (i.e., reduces BFP).

We estimate an analyst's exposure to transition-risk information three ways. First, we use the analysts' brown-industry work experience. Kadan et al. (2012) use the experience of the analysts in the industry they cover prior to becoming analysts as a proxy for industry knowledge and report that analysts with industry experience are more accurate than those without one. They argue that this indicates better information for industry-experienced analysts. Bradley, Gokkaya, and Liu (2017) similarly find that analysts with pre-analyst industry experience perform better than others. We calculate *Industry experience* as a dummy variable that equals 1 if the analyst has previously worked in a brown-industry firm. Second, we use the number of brown firms in the analyst's portfolio. The motivation is that analysts who cover brown firms are likely to have more information about transition risks. *Brown Firm Exposure* is the number of firms in high carbon intensity industries other than the focal firm followed by the analyst in the previous year. Finally,

we use the average environmental risk of firms covered by the analyst. *RepRisk* is the average environmental RepRisk Index score for firms covered by the analyst in the previous year. The motivation for *RepRisk* follows that for *Brown Exposure*: analysts with more environmentally unfriendly firms in their portfolio will have more transition-risk information.

In Table 7, the results from estimating Equation (5) for all three measures indicate that exposure to transition-risk information, rather than reducing BFP, exacerbates it. Columns (1), (2), and (3) correspond to the exposure proxy being *Brown Industry Experience*, *Brown Firm Exposure,* and *RepRisk*, respectively. In all three cases, the coefficients on both Scope 1 Emission and its interaction with exposure are negative and significant. The more exposure to transition risk information, the more pessimistic analysts are about brown firms. That exposure increases pessimism is consistent with Derrien et al. (2022), who examine the effect of ESG violation on analysts' forecasts and observe that analysts decrease their earnings forecast in all horizons in response to ESG violations. Additionally, Glossner (2021) documents that firms' past ESG incident rates predict more future incidents, weaker profitability, lower risk-adjusted stock returns, and larger analyst forecast errors.

[Table 7 about here]

The results in Table 7 appear to contradict the spirit of our earlier findings. In Table 4, we document that higher-quality analysts (i.e., star analysts or those with more experience) are less prone to BFP compared with their lower-quality peers. Here, however, we find the opposite: more informed analysts display greater pessimism. In particular, analysts with prior work experience in the industry they cover, who might be presumed to be higher quality, also exhibit increased BFP.

We suggest a plausible explanation for this finding. Within brown industries, the prevailing view is often that environmental measures are costlier than commonly perceived. Analysts who

have previously worked in such industries may internalize this pessimistic perspective, which then influences their research reports. This explanation is broadly consistent with, for example, Jennings and Markus (1984), who argue that political views are shaped significantly during adolescence and early adulthood. Related specifically to climate change, Spence, Poortinga, and Pidgeon (2011) find that experiencing extreme weather events in early adulthood increases concern about climate change and support for related policy action. Our interpretation suggests that early-life experiences can also work in the opposite direction. For instance, a young adult employed in a gold mine who is repeatedly exposed to narratives that climate policy poses a major threat to the industry may carry these beliefs into their later role as an analyst. This interpretation is consistent with Dong, Fisman, Wang, and Xu (2021), who show that analysts' recent personal experience visiting corporate sites during days of severe pollution can increase pessimism in their forecasts. A similar mechanism may apply here: analysts who frequently encounter ESG violations may become more pessimistic and overestimate the impact of such risks.

The above reasoning helps explain our seemingly contradictory results regarding experience and pessimism. Our findings suggest that greater overall experience leads to less BFP, whereas more experience specifically in covering brown firms is associated with greater BFP. We interpret this as follows: general experience reduces the likelihood of confusing a long-term increase in risk with a short-term decline in profitability. However, analysts who frequently cover brown firms are more likely to be exposed to the prevailing pessimistic views within those industries regarding environmental measures, views that may, in turn, amplify their pessimism.

Regardless of the reason for the heightened pessimism, the results here point to two important conclusions. The first is that the cohort of analysts that we previously deemed "higher-quality" appear to have an advantage in information processing, not information exposure, when

it comes to brown firms. The second is that with regards to climate change, additional information may lead to more pessimistic view about the effect of climate change on brown firms. Our results here contribute a financial angle to the ongoing debate about the role of information in climate change. Dickson (2005) and Ranney and Clark (2015) suggest that more information is likely to lead to a higher acceptance of climate change policies. Kellstedt et al. (2008) find the opposite, reporting that more information about climate change makes respondents less worried about climate change. Kahan et al. (2012) report a small decrease in perception of climate change risk when science literacy increases. According to our results, the claim that more dissemination of information will lead to more intervention could thus prove correct but not in the intended manner. More information could lead people to *overestimate* the costs of inaction, thereby leading to government action.

6. Conclusion

Sell-side analysts, who should be among the most informed financial professionals, appear ill-equipped to navigate the valuation complexities introduced by climate change. Our findings demonstrate systematic pessimism in analyst forecasts for high-emission firms—what we term brown-firm pessimism. Our results suggest that this pessimism is not rooted in strategic behavior or career incentives but instead stems from a recurring cognitive error: analysts mistakenly interpret increases in discount rates as declines in firm profitability, what we label as Denominator-to-Numerator Confusion (DNC).

This error is most prevalent among less experienced and non-star analysts, providing empirical support for a skill advantage for star analysts in Institutional Investor rankings. Strikingly, analysts with deeper exposure to brown industries are *more*, not less, likely to exhibit

BFP, suggesting that climate-specific information does not shield against climate-related valuation mistakes.

Our findings carry implications beyond analyst behavior. They underscore the challenge climate change poses to financial expertise, and caution that even well-informed agents may overreact to transition risk in the short term. As investors, regulators, and policymakers grapple with integrating climate risk into financial decision-making, understanding the nature and limits of analyst interpretation will be critical. An interesting question arising from our findings is whether, after establishing the link between climate change and discount factor (e.g. Engle et al, 2020), the mistake documented in this paper will decrease or even disappear.

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Table 1: Summary Statistics

This table reports summary statistics. Forecast Error is the difference between the annual EPS forecast and the realized annual EPS, scaled by the price on the trading day prior to the forecast announcement date. *Scope 1 (industry)* is the natural logarithm of SIC3 industry Scope 1 carbon intensity, defined as total Scope 1 carbon emissions of firms in the same industry divided by the total revenue of firms in the same industry. *Residual Scope 1 (firm)* is the residual of regressing *Scope 1 (firm)*, defined as the natural logarithm of the firm's Scope 1 carbon emissions divided by revenue at the firm level, on *Scope 1 (industry)*. Both *Scope 1 (industry)* and *Residual Scope 1 (firm)* are normalized to have a mean of 0 and a standard deviation of 1. *Horizon* is the natural logarithm of the number of months between the forecast period date and announcement date. *General experience* is the natural logarithm of the number of months since an analyst appeared in the IBES. *Firm experience* is the natural logarithm of the number of months since an analyst covered a firm. *Broker size* is the natural logarithm of the number of analysts at a brokerage. *# of firms followed* is the natural logarithm of the number of firms followed by an analyst. *# of reports issued* is the natural logarithm of the number of reports about a firm. *Analyst coverage* is the natural logarithm of the number of analysts following a firm. *Firm size* is the natural logarithm of total assets. *Tobin's Q* is the market value of assets divided by the book value of assets. *Profitability* is operating income before depreciation divided by total assets. *Intangible assets* is the ratio of intangible assets to total assets. *Stock return* is the cumulative stock return over the past year. *Equity volatility* is the natural logarithm of the standard deviation of monthly stock returns over the past year. *Trading volume* is the natural logarithm of the total trading volumes of a stock over the past year. We cluster standard errors at the analyst, industry, and year-month levels, and display them in parentheses. Significance at the 10%, 5% and 1% levels are indicated by *, ** and *** respectively.

	Mean	Std. Dev.	25%	50%	75%
Forecast Error	0.0056	0.0332	-0.0054	0.0000	0.0090
Scope 1 (industry)	0.0000	1.0000	-0.3582	0.1949	0.5641
Residual Scope 1 (firm)	0.0000	1.0000	-0.7168	-0.1590	0.5691
Tobin's Q	2.1369	1.4927	1.1870	1.6361	2.4656
Profitability	0.1190	0.1152	0.0715	0.1212	0.1760
Intangible assets	0.2004	0.2133	0.0177	0.1206	0.3414
Stock return	0.1240	0.4029	-0.1157	0.0946	0.3092
Analyst coverage	2.1430	0.6410	1.7918	2.1972	2.5649
# of firms followed	1.8578	0.9131	1.3863	2.0794	2.4849
# of reports issued	2.0172	1.0210	1.6094	2.1972	2.7081
Firm size	8.9048	1.6973	7.7968	8.8491	9.9978
Broker size	3.8112	1.0808	3.0445	3.9120	4.7185
Horizon	2.2772	0.4049	2.3026	2.3979	2.4849
General experience	4.3621	1.3902	3.7842	4.6913	5.4161
Firm experience	2.9132	1.7170	1.7918	3.3673	4.2485
Equity volatility	-2.4871	0.4973	-2.8472	-2.5093	-2.1482
Trading volume	15.2763	1.2888	14.4625	15.3051	16.1373

Table 2: Carbon Intensity and Analyst Optimism

This table report the regression results for the baseline analysis, observed at the individual forecast level for the period 2005-2019. *Forecast Error* is the difference between the annual EPS forecast and the realized annual EPS, scaled by the price on the trading day prior to the forecast announcement date. *Scope 1 (industry)* is the natural logarithm of SIC3 industry Scope 1 carbon intensity, defined as total Scope 1 carbon emissions of firms in the same industry divided by the total revenue of firms in the same industry. *Residual Scope 1 (firm)* is the residual of regressing *Scope 1 (firm)* on *Scope 1 (industry)*, where *Scope 1 (firm)* is the natural logarithm of firm Scope 1 carbon intensity, defined as Scope 1 carbon emissions divided by revenue at the firm level. We cluster standard errors at the analyst, industry, and year-month levels, and display them in parentheses. Significance at the 10%, 5% and 1% levels are indicated by *, ** and *** respectively. For brevity, constants are not reported.

Dependent Variable = Forecast Error				
	(1)	(2)	(3)	(4)
Scope 1 (industry)	-0.0045**	-0.0034**		-0.0039**
	(0.0019)	(0.0016)		(0.0017)
Residual Scope 1 (firm)			0.0000	-0.0004
			(0.0004)	(0.0004)
Horizon		0.0041***	0.0041***	0.0041***
		(0.0007)	(0.0007)	(0.0007)
General experience		0.0003	0.0003	0.0003
		(0.0002)	(0.0002)	(0.0002)
Firm experience		0.0001*	0.0001	0.0001*
		(0.0001)	(0.0001)	(0.0001)
Broker size		0.0001	0.0001	0.0001
		(0.0004)	(0.0004)	(0.0004)
# of firms followed		-0.0005	-0.0005	-0.0005
		(0.0008)	(0.0008)	(0.0008)
# of reports issued		0.0004	0.0004	0.0004
		(0.0007)	(0.0007)	(0.0007)
Analyst coverage		-0.0005	-0.0005	-0.0005
		(0.0007)	(0.0007)	(0.0007)
Firm size		0.0059***	0.0059***	0.0058***
		(0.0013)	(0.0013)	(0.0013)
Market-to-book		0.0001	0.0001	0.0001
		(0.0003)	(0.0003)	(0.0003)
Profitability		0.0289***	0.0295***	0.0288***
		(0.0093)	(0.0089)	(0.0092)
Intangible assets		0.0003	0.0003	0.0002
		(0.0024)	(0.0025)	(0.0024)
Stock return Equity		-0.0078***	-0.0078***	-0.0078***
		(0.0015)	(0.0015)	(0.0015)
Volatility		0.0021*	0.0020*	0.0020*
		(0.0011)	(0.0011)	(0.0011)
Trading volume		-0.0001	-0.0001	-0.0000
		(0.0008)	(0.0008)	(0.0008)
Observations	239,686	229,810	229,582	229,582
R-squared	0.2892	0.3037	0.3036	0.3038
Year-Month FE	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes
Broker FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 3: Political Affiliation

The dependent variable is *Forecast Error*, defined as the difference between the annual EPS forecast and the realized annual EPS, scaled by the price on the trading day prior to the forecast announcement date. *Scope 1 (industry)* is the natural logarithm of SIC3 industry Scope 1 carbon intensity, defined as total Scope 1 carbon emissions of firms in the same industry divided by the total revenue of firms in the same industry. *Pro-Republican brokerage I* is a dummy variable that equals 1 if the employees of a brokerage house primarily donate to the Republicans. *Pro-Republican brokerage II* is a dummy variable that equals 1 if the PACs of a brokerage house primarily donate to the Republicans. The analyst-specific controls are as defined in Table 2. We cluster standard errors at the analyst, industry, and year-month levels, and display them in parentheses. Significance at the 10%, 5% and 1% levels are indicated by *, ** and *** respectively.

Dependent Variable = Forecast Error

	(1)	(2)
Scope 1 (industry) × Pro-Republican brokerage I	-0.0004	
	(0.0003)	
Scope 1 (industry) × Pro-Republican brokerage II		0.0007
		(0.0009)
Scope 1 (industry)	-0.0032*	-0.0037*
	(0.0016)	(0.0021)
Controls	Yes	Yes
Observations	184,559	82,430
R-squared	0.3044	0.3117
Year-Month FE	Yes	Yes
Analyst FE	Yes	Yes
Broker FE	Yes	Yes
Firm FE	Yes	Yes

Table 4: Is the Pessimism a Deliberate Action?

Logistic regression results for analyst career outcomes. Models (1)-(2) examine the probability of becoming star analysts. Model (3) examines the probability of an analyst exiting the IBES database, with the sample limited to analysts whose *General experience* is below the full-sample median. Model (4) examines the probability of moving to a larger brokerage house. *Pessimism about "brown" industry* is the analyst-year level average of indicators that equal 1 if *Forecast Error* is in the bottom quintile for a covered firm that belongs to a high carbon intensity industry. *Pessimism* is the analyst-year level average of indicators that equal 1 if *Forecast Error* is at the bottom quintile for a covered firm. *"Brown" industry* refers to the analyst-year level average of indicators that equal 1 if a covered firm belongs to a high carbon intensity industry. *Forecast error* is the absolute value of the analyst-year level average of *Forecast Error*. The analyst-specific controls are as defined in Table 2. We cluster standard errors at the analyst level and display them in parentheses. Significance at the 10%, 5% and 1% levels are indicated by *, ** and *** respectively.

Dependent Variable =	Star analyst (Top 1)	Star analyst (Top 4)	Exit	Move-up
	(1)	(2)	(3)	(4)
"Brown" Pessimism	-0.1279	0.0898	0.0842	-0.9731
	(0.4857)	(0.2146)	(0.1883)	(0.9014)
Pessimism	0.0150	-0.1039	0.1261	0.4369
	(0.2230)	(0.1111)	(0.0937)	(0.2663)
"Brown" industry	-0.0852	-0.1811	0.0113	-0.0538
	(0.2991)	(0.1646)	(0.0760)	(0.2706)
Absolute Forecast error	-5.1416**	-6.1731***	-0.1073	1.6591
	(2.1370)	(1.3755)	(0.4873)	(1.3190)
General experience	0.6796***	0.6600***	-0.0573***	-0.0639
	(0.1022)	(0.0563)	(0.0212)	(0.0558)
Broker size	0.9190***	1.2558***	-0.0372*	0.0970*
	(0.1181)	(0.0761)	(0.0204)	(0.0542)
# of firms followed	0.2299	0.6417***	-0.3159**	-0.1811
	(0.4153)	(0.2007)	(0.1598)	(0.4689)
# of reports issued	-0.1727	-0.3818**	0.0628	0.1057
	(0.3710)	(0.1752)	(0.1396)	(0.4059)
Observations	29,788	29,788	12,778	25,161
Year Dummies	Yes	Yes	Yes	Yes

Table 5: The Role of Analyst Quality

In all tests, the dependent variable is *Forecast Error*, defined as the difference between the annual EPS forecast and the realized annual EPS, scaled by the price on the trading day prior to the forecast announcement date. *Scope 1 (industry)* is the natural logarithm of SIC3 industry Scope 1 carbon intensity, defined as total Scope 1 carbon emissions of firms in the same industry divided by the total revenue of firms in the same industry. *Star analyst (top 1)* is a dummy variable that equals one if an analyst is ranked the first by the Institutional Investor magazine in the previous year. *Star analyst (top 4)* is a dummy variable that equals one if an analyst is selected as the first or runner-ups by the Institutional Investor magazine in the previous year. *General experience* is the natural logarithm of the number of months since an analyst appeared in the IBES. *Firm experience* is the natural logarithm of the number of months since an analyst covered a firm. The analyst-specific controls are as defined in Table 2. We cluster standard errors at the analyst, industry, and year-month levels, and display them in parentheses. Significance at the 10%, 5% and 1% levels are indicated by *, ** and *** respectively.

Panel A: Quality = Star Status
Dependent Variable = Forecast Error

	(1)	(2)
Scope 1 (industry) × Star analyst (Top 1)	0.0023**	
	(0.0012)	
Star analyst (top 1)	0.0012	
	(0.0010)	
Scope 1 (industry) × Star analyst (Top 4)		0.0016**
		(0.0007)
Star analyst (top 4)		-0.0008
		(0.0007)
Scope 1 (industry)	-0.0035**	-0.0036**
	(0.0016)	(0.0017)
Controls	Yes	Yes
Observations	229,810	229,810
R-squared	0.3038	0.3038
Year-Month FE	Yes	Yes
Analyst FE	Yes	Yes
Broker FE	Yes	Yes
Firm FE	Yes	Yes

Panel B: Quality = Analyst Experience

Dependent Variable = Forecast Error

	(1)	(2)
Scope 1 (industry) × General experience	0.0009***	
	(0.0003)	
Scope 1 (industry) × Firm experience		0.0009***
		(0.0002)
Scope 1 (industry)	-0.0035**	-0.0036**
	(0.0016)	(0.0016)
Controls	Yes	Yes
Observations	229,810	229,810
R-squared	0.3039	0.3041
Year-Month FE	Yes	Yes
Analyst FE	Yes	Yes
Broker FE	Yes	Yes
Firm FE	Yes	Yes

Table 6: BFP, Cost of Equity and Past returns

The dependent variable is *Forecast Error*, defined as the difference between the annual EPS forecast and the realized annual EPS, scaled by the price on the trading day prior to the forecast announcement date. *Scope 1 (industry)* is the natural logarithm of SIC3 industry Scope 1 carbon intensity, defined as total Scope 1 carbon emissions of firms in the same industry divided by the total revenue of firms in the same industry. Δ *Cost of Equity* is the annual change in a composite measure of a firm's cost of equity. *Low Stock return* is a dummy variable that equals one if the annual stock return of the firm in the previous year is in the bottom decile. *WSJ CC Index* is the average monthly WSJ Climate Change News Index over the past year (Engle et al., 2020). The analyst-specific controls are as defined in Table 2. We cluster standard errors at the analyst, industry, and year-month levels, and display them in parentheses. Significance at the 10%, 5% and 1% levels are indicated by *, ** and *** respectively. In (3), WSJ Climate change news is not included as it is collinear with the year-month fixed effects.

	Dependent Variable = Forecast Error		
	(1)	(2)	(3)
(Δ)Cost of Capital =	Δ Cost of Equity	Low Stock return	WSJ CC Index
Scope 1 (industry) × (Δ)Cost of Capital	-0.0008*	-0.003*	-0.0009*
	-0.0005	-0.0018	-0.0005
(Δ)Cost of Capital	0.0016***	0.0181***	
	-0.0005	-0.002	
Scope 1 (industry)	0.0009	-0.0029*	-0.001
	-0.0012	-0.0016	-0.0016
Controls	Yes	Yes	Yes
Observations	129,551	229,638	172,014
R-squared	0.2931	0.3206	0.2997
Year-Month FE	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes
Broker FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Table 7: Exposure to Climate-related Information

The dependent variable is *Forecast Error*, defined as the difference between the annual EPS forecast and the realized annual EPS, scaled by the price on the trading day prior to the forecast announcement date. *Scope 1 (industry)* is the natural logarithm of SIC3 industry Scope 1 carbon intensity, defined as total Scope 1 carbon emissions of firms in the same industry divided by the total revenue of firms in the same industry. *Exposure to "brown" firms I* is the average environmental RepRisk Index of firms covered by an analyst in the previous year. *Exposure to "brown" firms II* is the number of firms in high carbon intensity industries other than the focal firm followed by an analyst in the previous year. *"Brown" industry experience* is a dummy variable that equals 1 if an analyst has worked in environmentally-unfriendly industries. The analyst-specific controls are as defined in Table 2. We cluster standard errors at the analyst, industry, and year-month levels, and display them in parentheses. Significance at the 10%, 5% and 1% levels are indicated by *, ** and *** respectively. "Brown" industry experience in (1) is dropped out of the regression as it is collinear with the analyst fixed effects.

Dependent Variable = Forecast Error			
	(1)	(2)	(3)
Scope 1 (industry) × "Brown" industry experience	-0.0041**		
	(0.0019)		
Scope 1 (industry) × "Brown" Firm Exposure		-0.0003*	
		(0.0002)	
Scope 1 (industry) × RepRisk			-0.0004**
			(0.0002)
Scope 1 (industry)	-0.0043*	-0.0034**	-0.0041**
	(0.0023)	(0.0016)	(0.0019)
"Brown" Firm Exposure		0.0002	
		(0.0002)	
RepRisk			0.0006*
			(0.0004)
Controls	Yes	Yes	Yes
Observations	82,118	229,810	168,883
R-squared	0.3057	0.3037	0.3125
Year-Month FE	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes
Broker FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Appendix: Variable Definitions

Variable Name	Definition
Forecast error	Difference between the initial annual EPS forecast and the subsequently realized annual EPS, scaled by the price on the trading day prior to the forecast announcement date.
Scope 1 (industry)	Natural logarithm of SIC3 industry Scope 1 carbon intensity, defined as total Scope 1 carbon emissions of firms in the same industry divided by the total revenue of firms in the same industry.
Scope 1 (firm)	Natural logarithm of firm Scope 1 carbon intensity, defined as Scope 1 carbon emissions divided by revenue at the firm level.
Residual Scope 1 (firm)	Residual from regressing *Scope 1 (firm)* on *Scope 1 (industry)*.
Tobin's Q	Market value of assets divided by the book value of assets.
Profitability	Operating income before depreciation divided by total assets.
Intangible assets	Ratio of intangible assets to total assets.
Stock return	Cumulative stock return over the past year.
Analyst coverage	Natural logarithm of the number of analysts following a firm.
# of firms followed	Natural logarithm of the number of firms followed by an analyst.
# of reports issued	Natural logarithm of the number of reports about a firm.
Firm size	Natural logarithm of total assets. *Profitability* is operating income before depreciation divided by total assets.
Broker size	Natural logarithm of the number of analysts at a brokerage.
Horizon	Natural logarithm of the number of months between the forecast period date and announcement date.
General experience	Natural logarithm of the number of months since an analyst appeared in the IBES.
Firm experience	Natural logarithm of the number of months since an analyst covered a firm.
Equity volatility	Natural logarithm of the standard deviation of monthly stock returns over the past year.
Trading volume	Natural logarithm of the total trading volumes of a stock over the past year.
Pro-Republican brokerage I	Dummy variable that equals 1 if the employees of a brokerage house primarily donate to the Republicans.
Pro-Republican brokerage II	Dummy variable that equals 1 if the PACs of a brokerage house primarily donate to the Republicans.
Star analyst (top 1)	Dummy variable that equals one if an analyst is ranked the first by the Institutional Investor magazine in the previous year.
Star analyst (top 4)	Dummy variable that equals one if an analyst is selected as the first or runner-ups by the Institutional Investor magazine in the previous year.
WSJ Climate change news	Average monthly WSJ Climate Change News Index over the past year (Engle et al., 2020).
"Brown" industry experience	Dummy variable that equals 1 if an analyst has worked in environmentally-unfriendly industries.

RepRisk	The average environmental RepRisk Index of firms covered by an analyst in the previous year.
"Brown" Firm Exposure	Number of firms in high carbon intensity industries other than the focal firm followed by an analyst in the previous year.
Pessimism about "brown" industry	The analyst-year level average of indicators that equal 1 if *Forecast Error* is at the bottom quintile for a covered firm that belongs to a high carbon intensity industry
Pessimism	Analyst-year level average of indicators that equal 1 if *Forecast Error* is at the bottom quintile for a covered firm
Absolute Forecast error	Absolute value of the analyst-year level average of *Forecast Error*
"Brown" industry	Analyst-year level average of indicators that equal 1 if a covered firm belongs to a high carbon intensity industry
Δ *Cost of Equity*	Annual change in the cost of equity, defined as the average of the cost of equity capital estimates in Claus and Thomas (2001), Gebhardt, Lee and Swaminathan (2001), Easton (2004) and Ohlson and Juettner-Nauroth (2005).
Cost of equity capital estimates in Claus and Thomas (2001)	Cost of capital proxy following Claus and Thomas (2001): $P_0 = B_0 + \sum_{n=1}^{5} \frac{AE_{t+n}}{(1+r_{CT})^n} + \frac{AE_{t+5}(1+g_p)}{(r_{CT}-g_p)(1+r_{CT})^5}$, where $AE_{t+n} = EPS_{t+n} - r_{CT}*BV_{t+n-1}$ and g_p is the perpetual growth rate.
Cost of equity capital estimates in Gebhardt, Lee, and Swaminathan (2001)	Cost of capital proxy following Gebhardt, Lee, and Swaminathan (2001) $$P_0 = B_0 \sum_{t=1}^{11} \frac{(EPS_t - r_{GLS})B_{t-1}}{(1+r_{GLS})} + \frac{(EPS_{12} - r_{GLS})B_{11}}{r_{GLS}(1+r_{GLS})^{11}}$$
Cost of equity capital estimates in Easton (2004)	Cost of capital proxy following Easton (2004): $r_{MPEG} = \sqrt{\frac{EPS_2 - r_{MPEG}*DPS_1 - EPS_1}{P_0}}$
Cost of equity capital estimates in Ohlson and Juettner-Nauroth (2005)	Cost of capital proxy following Ohlson and Juettner-Nauroth (2005): $r_{OJN} = A + \sqrt{A^2 + \frac{EPS_1}{P_0}(\frac{EPS_2 - EPS_1}{EPS_1} - (\gamma - 1))}$, where $A = \frac{1}{2}\left((\gamma - 1) + \frac{DPS_1}{P_0}\right)$ and γ-1 is the perpetual growth rate, g_p.

Declaration of interests

☒The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: