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

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Abstract

Estimating the financial implications of climate change on corporate profitability is a formidable analytical challenge—one that inherently aligns with sell-side analysts' specialized expertise. We investigate analysts' performance in this endeavor and find that analysts exhibit heightened pessimism in their earnings projections for carbon-intensive firms relative to actual realized earnings, a phenomenon we designate as "brown-firm pessimism". Our empirical analysis suggests that this pessimism is likely a fundamental error, one in which analysts conflate elevated discount rates with diminished earnings prospects. Paradoxically, we find that brown-firm pessimism is even higher for analysts with prior professional experience in pollution-intensive industries, suggesting that more exposure to brown-firm information amplifies rather than attenuate the analytical misconception.

1. Introduction

Climate change poses a novel and complex challenge to investors. Consider, more precisely, the task of accounting for climate change's future effects on a firm's cash flows. This endeavor demands projecting, at a minimum, the magnitude of climate change, the firm's exposure to such 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 unprecedented in investment history. As transition risk becomes increasingly central for corporate valuations, a crucial question emerges: How effectively do investors assess this risk? One group that is particularly well-equipped to navigate this sophisticated financial computation is sell-side analysts. Sell-side analysts are highly specialized, often covering a small number of stocks within a single industry, and would consequently be among the most well-informed regarding the likely effects of climate change at the individual firm level.

In this paper, we examine how effectively sell-side analysts evaluate transition risk through the lense of their annual earnings forecast error, a metric that directly reflects transition risk's financial impact. By focusing on one-year intervals, we assess analysts not on the arduous challenge of estimating a firm's complete transition risk profile, but rather on their ability to estimate its immediate- -term implications. In this regard, we contend that annual forecast errors serve as the most relevant and equitable performance indicator.

Employing this observable, ex-post metric and classifying firms' environmental impact by their industry emissions, we find that the browner the firm, the more pessimistic the analysts are in their forecasts relative to the actual earnings. Subsequent analysis suggests that this pessimistic

bias represents a methodological error rather than a deliberate strategic choice. We advance a novel mechanism to explain this mistake – specifically, that analysts erroneously conflate higher discount rate with diminished expected cash flows – and find supportive evidence in the data. Finally, we ask whether exposure to climate-related information can ameliorate this pessimism and find, perhaps counterintuitively, that such exposure actually intensifies the pessimism.

Empirically, for each analyst-stock-year triplet, we assess forecasting accuracy by computing the annual earnings per share (EPS) forecast error as the difference between the analyst's first full-year EPS forecast and the realized annual EPS for a given firm and financial year, scaled by the share price one day before the forecast is announced. We employ signed forecast errors to address the question posed in the title of our paper: Are analysts up to the challenge of climate change? Our baseline tests examines whether forecast errors correlate with firms' environmental impact. Following the methodological framework established by Ilhan et al. (2021) and Bolton and Kacperczyk (2021), we measure corporate environmental impact through industry-level emissions rather than individual firm emissions, as the latter exhibits excessive volatility. We find that Scope 1 emissions are negatively and significantly correlated with forecast errors: The browner the firm is, the more pessimistic the earnings forecasts are relative to the ultimately realized earnings.[1] We henceforth refer to this phenomenon as "brown-firm pessimism", or "BFP". This result extends previous literature that show that analysts turn pessimistic after being exposed to (e.g.) severe weather events (Pankratz, Bauer, and Derwall, 2023) and shows that not only extreme events are salient to analysts' estimates of transition risk but also slow-moving state variables matter.

[1] Relatedly, Cheng (2024) finds that analyst pessimism is higher for geographically proximate polluting firms relative to non-polluters.

That analysts' forecasts exhibit BFP is not evidence that analysts perform worse at forecasting the earnings of brown firms, as the pessimism may be intentional. To determine whether this is the case, we undertake three lines of investigation. The first is based on the supposition that BFP is a deliberate strategy to align the analyst's forecast to the politics of their brokerage. We categorize the brokerage house's political orientation by its political action committee ("PAC") contributions. We then test whether BFP is correlated with the brokerage house's politics and 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, BFP is not significantly correlated with the tested career outcome, inconsistent with the hypothesis that that personal benefits drive BFP. 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 less frequent for skilled 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] We find 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.

[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.

The preceding results indicate that sell-side analysts are more pessimistic for browner firms and suggest that this pessimism is a mistake and not strategic. 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. A key point of this hypothesis is that the confusion is limited to brown firms. Climate change as a risk factor has been discussed only recently (e.g., Engle et al., 2020), whereas traditional risk factors (e.g., beta and book-to-market) have been known for decades. 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.

Testing the DNC hypothesis requires proxying for the climate change risk factor and then determining whether analysts are more pessimistic conditional on changes in the level of the risk factor. We test three different proxies. The first is the average monthly WSJ Climate Change News Index over the past year, with higher realizations proxying for increases in discount rates for brown firms. The rationale for this is based on Engel et al. (2020), who argue that for brown firms, a change in the amount of climate change news is positively correlated with the contemporaneous change in the discount factor. The second proxy is the annual change in a composite cost of equity capital estimate for each firm, calculated using four established methods from the literature. The final proxy is an indicator variable, *Low Stock Return,* equal to one if the trailing one-year return for the firm is in the bottom decile of all stocks for that year. When we regress forecast errors on the interaction of Scope 1 emissions and the proxies for changes in the level of the discount rate, we find that for brown firms only, analysts tend to be more pessimistic when the firm's discount

increased. The results are consistent with the DNC hypothesis that analysts conflate increases in the discount rate with decreases in earnings for brown firms.

If BFP is a mistake, can an intervention ameliorate it? While our earlier findings suggest that higher-caliber analysts demonstrate reduced pessimism, we explore whether this superior performance stems from enhanced information access or more sophisticated analytical capabilities. A common presumption in economics and beyond is that the more information an agent has, the better their estimates will be. We use three proxies for an analyst's exposure to transition risk information – their preanalyst work experience in brown firms, the number of brown firms in their portfolio, and average environmental risk score of the firms in their portfolio – and find that, rather counterintuitively, more exposure *exacerbates* BFP rather than attenuates it. The findings here point to two important conclusions. First, more information about brown firms appears to make analysts overestimate even the short-term costs associated with climate change policies. Second, high-quality analysts seem to be defined by their ability to process their information rather than by the amount of knowledge they possess.

Our paper makes several contributions. First, we add to the literature on financial intermediaries and climate change. Where prior literature has largely been interested how intermediaries price climate risk (Bolton and Kazperczyk, 2021 and 2023; Hsu, Li and Tsou, 2023; Ardia, Bluteau, Boudt, and Inghelbrecht, 2023), we look directly at how well an influential subset of intermediaries – analysts – estimate the actual costs associated with that risk. A related literature examines how proximity and/or exposure to climate risk affects investors' decisions (e.g, Alok, Kumar, and Wermers, 2020). More directly related to our paper is Cuculiza, Kumar, Xin, and Zhang (2022), who look at analysts' forecasts but in the context of the analyst's proximity to firms with high sensitivity to abnormal temperature changes. Our innovation is to use earnings forecasts

to determine how well an important subset of investors' advisors – financial analysts – can distill transition risk into a bottom-line number. Estimating the full scope of a firm's transition risk is an extraordinarily complex task, and by limiting the forecast horizon to a year, we evaluate analysts on the narrowest and, we believe, fairest portion of that task.

Our second contribution is related to the effect of information on the cost of climate change policies. Heterogeneity in analysts' quality is associated with different levels of brown-firm pessimism, and we ask whether the underlying mechanism is heterogeneity in analysts' information sets. We find that analysts with more exposure to information about brown industries are more pessimistic about the earnings of polluting firms. That is, exposure drives pessimism. Various papers (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. Our results support the proposition but not in the intended manner: more information may lead to overestimates of the potential costs, which in turn should drive stricter climate change policies.

Finally, we add to the literature on star analysts and whether they are more skilled than their non-star counterparts. We document that, unlike their non-star counterparts, star analysts forecast brown firms with the same ability as they do non-brown firms, consistent with the notion that star analysts being more skilled than others (Stickel, 1992; Fang and Yasuda, 2014; Aharoni et al., 2023).

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 are negatively correlated 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. Similarly, 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 recommendation 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

Could BFP be an artifact of political affiliations? 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 in which subjects are presented with a timeseries graph of global temperatures and self-identified conservatives focus on the flat, pre-1980 portion while self-identified liberals focus on the upward-sloping, post-1980 portion. Similar observations have been documented in financial settings. Many papers document 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 to ask 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 because they aim to be consistent with their firm's ideology.

Before any formal analysis, however, there are reasons to be skeptical of a political explanation. Our focus on 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 from 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 driven in part 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.

We regress forecast errors on *Scope 1 (Industry)* and the interaction of *Scope 1 (Industry)* and the political affiliation dummy variable. The results, presented in Table 3, do not suggest that brown-firm pessimism 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.[3]

[Table 3 about here]

3.2.2 Career Concerns

The political affiliations hypothesis is premised on the idea that analysts have goals that are not limited to, say, minimizing forecast errors. 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 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 document 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 will use two metrics here. One corresponds to an analyst being ranked the top in any All-American category, and the other corresponds to an analyst being ranked in the top four of any category.

[3] 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.

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 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 $\text{Career}_{i,t+1}$ 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 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 test for this using two separate proxies for an analyst's quality: their Institutional Investor all-star status and their experience as an analyst.

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.

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 for this assumption, 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 observe 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 with a 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 more accumulated 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.

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 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:

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

Negative coefficients on both *Scope1Industry* and the interaction term would suggest that BFP is more severe when the (brown) firm's discount rate has increased, consistent with DNC hypothesis.

We identify three proxies for changes in discount rates. First, we estimate *WSJ Climate Change News* as the average monthly *Wall Street Journal* Climate Change News Index over the past year. Engle et al. (2020) argue that a high volume of climate change news is correlated with increase in the risk of brown firms, as the likelihood of environmental regulation increases. The DNC hypothesis accordingly implies that during these periods, analysts will be more pessimistic about the earnings of brown firms. Second, we calculate *Annual Change in CC* as 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).[4] Where the WSJ index is essentially a state variable, this measure is specific to each firm, allowing us to separate between (e.g.) brown firms that are likely to experience an increase in their discount rate and those that are not. Third, we use a decrease in stock

[4] See Appendix A for detailed explanations of the four cost of equity capital measures.

prices to proxy for firms that analysts are more likely make the denominator-to-numerator mistake. *Low Stock Return* is a dummy variable equal to 1 if the stock's previous annual return was in the lowest decile of all stock returns for that year.

The results in Table 6 for all three discount rate proxies support the DNC hypothesis. For *WSJ Climate Change News*, the coefficient on the interaction variable of *Scope1Industry* and the index is 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, with earnings estimates that are too low. 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 *Annual Change in CC*, we find a similar result. The coefficient on the interaction term is negative and significant, implying as brown firms' discount rates increase, BFP is more severe, consistent with the DNC hypothesis. And again, the coefficient on *Scope1Industry* alone is not significant. Finally, *Low Stock Return*, the coefficient on the interaction term again remains negative and significant, consistent with the DNC hypothesis.

[Table 6 about here]

Cumulatively, the results in Table 6 are consistent with 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 *Annual Change in CC* and *Low Stock Return* cast doubt on this. That analysts are making a larger mistake when covering firms that suffer an increase in their discount factor compared to those firms that do not suffer such an increase diminishes the likelihood that analysts' characteristics drive BFP.

5. Exposure to Information

Insofar as BFP is a mistake, a natural question to ask is whether there is an intervention to ameliorate it. The results in Section 3.2.3 showing that higher-quality analysts (stars/experienced) suffer less from BFP than other analysts 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 (Luís, Vauclair, and Lima, 2018; Halady and Rao, 2010). If, on the other hand, these "quality" analysts – and in particular, star analysts – have a *skill* advantage, their observed superiority with regard to BFP would be driven by 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. A positive result would support the notion that higher-quality analysts have an informational advantage with regards to brown firms. A negative result would support the notion that higher-quality analysts have superior skills outside the realm of their brown-firm information sets.

We regress 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 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 perversely reduce the individual's understanding of the true costs of inaction. Our paper contributes 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 and report 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.

We can only speculate as to why more information appears to make analysts more pessimistic about brown firms. One possibility is that the more exposed the analyst is to information about climate risks, the more weight they put on the most negative subsets of information about climate change and its likely impact on brown firms' earnings. Another possibility is that BFP is related to other factors that bias the earnings prediction of brown firms but do not directly relate to the estimation of the cost of climate change policies. These factors

could include overestimation of the probability that measures with short-term effects may be approved, overestimation of the effect of the shift in public opinion related to climate on firms' policy, and underestimation of the firms' ability to mitigate the financial effect of future policies through legal loopholes. Many of these factors are outside the typical expertise of analysts, potentially suggesting a higher likelihood of a mistake. One plausible difference between stars and ordinary analysts is that star analysts are better at estimating these peripheral factors and thus are more accurate. Ultimately, we do not take a stance given the limitations of the available data.

6. Conclusion

Our paper investigates how well analysts estimate the transition-risk costs associated with climate change. One of the key questions with climate change is its cost, and at the firm level, analysts are natural candidates to address this question given their expertise in specific industries. Our findings suggest, however, that analysts cannot tackle the complexity of transition risk and on average overestimate its associated costs, over even the short, one-year horizon that we measure. Specifically, we document that forecast errors are systematically more negative for browner firms, a phenomenon we refer to as Brown Firm Pessimism (BFP). Further tests indicate that BFP is likely not strategic but rather a mistake.

There are several key takeaways from our paper. First, our documentation of BFP represents a novel approach to literature on climate change and investors. Prior literature has primarily examined the pricing of transition risk or investors' allocations in response to climate risk. Ours is the first to examine the ex-post performance of agents' predictions regarding climate-sensitive firms.

Second, and somewhat counterintuitively, we document that for lower-quality analysts, BFP is exacerbated by exposure to transition-risk information rather than attenuated by it. This result presents a challenge to the notion, both within the discussion of climate change and beyond it, that more information is an unalloyed good. We provide evidence that more exposure to transition-risk information yields worse estimates for browner firms. The perhaps ironic silver lining is that even if more exposure causes individuals to overestimate the costs of climate change, more exposure should spur mitigating actions demanded by an overly pessimistic populace.

Finally, we find that BFP is diminished for those analysts who we deem "higher quality" – star analysts and more experienced analysts. Additional tests suggest that their advantage lies not in their additional exposure to information but rather in their ability to process the same information more accurately than other, lower-quality analysts.

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Aharoni Lim Litov etc All Star Paper

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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
Proftitability	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 Mistake or 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 Research 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: Analysts' Pessimism, 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. *WSJ CC Index* is the average monthly WSJ Climate Change News Index over the past year (Engle et al., 2019). 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. 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 (1), 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	WSJ CC Index	Δ Cost of Equity	Low Stock return
Scope 1 (industry) × (Δ)Cost of Capital	-0.0009*	-0.0008*	-0.003*
	(0.0005)	(0.0005)	(0.0018)
(Δ)Cost of Capital		0.0016***	0.0181***
		(0.0005)	(0.0020)
Scope 1 (industry)	-0.001	0.0009	-0.0029*
	(0.0016)	(0.0012)	(0.0016)
Controls	Yes	Yes	Yes
Observations	172,014	129,551	229,638
R-squared	0.2997	0.2931	0.3206
Year-Month FE	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes
Broker FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Table 7: The Role of 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 Table: Variable Definitions

Variable Name	**Variable 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., 2019).
"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, $g_{p.}$