Salient Cues of Economic Transitions in Analyst Forecasting: Evidence from the Electric Vehicle Era

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Abstract

How do financial intermediaries recognize shifting business models and investor priorities? In the context of the green transition, we show that salient cues of broad economic trends shape financial analysts' attention and effort. Analysts in high-salience areas revise green firm forecasts more frequently, show greater climate-related engagement during earnings calls, and increase opportunity-oriented climate language in reports. Their resulting increased forecast accuracy for green firms reflects not a net gain in forecasting ability, but a reallocation of limited attention and effort. Markets respond more to their green-firm forecast revisions, and the information environment of green firms improves under their coverage.

Keywords: Financial analysts; limited attention; effort allocation; salient cues; green firms
JEL Classification Codes: G14, G29, M41, Q20

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DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the authors used Claude to assist with copyediting certain portions of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

I. INTRODUCTION

Security analysts play a critical role in the dissemination of information in financial markets. Their forecasts and recommendations are closely followed by investors, and thus serve as a key channel through which firm-related information is incorporated into asset prices. Prior research has shown that analysts do not allocate their limited time and cognitive resources equally across all firms covered by them. Instead, they strategically allocate greater effort to firms that are more important to their career outcomes or institutional clients, such as firms with higher market capitalization or greater institutional ownership (e.g., Harford, Jiang, Wang, and Xie, 2019). This literature views effort allocation primarily as a function of firm characteristics.

However, business models and investor focus can shift, reflecting large-scale changes such as the advent of the Internet, blockchain technology, ESG broadly, or the green transition specifically. Thus, in this study, we hypothesize that analysts' effort allocation should also respond to broader economic trends or opportunities that shape the business environment, as reflected in dynamic contextual cues, which are not specific to any particular firm. We ask whether salient cues local to the analyst contribute to analysts' decisions about how to prioritize their attention and analytical capacity across covered firms.

We explore this hypothesis in the context of rising interest in the green transition by examining how local electric vehicle (EV) adoption—used as a proxy for the salience of the green transition—affects analysts' forecasting behavior and accuracy. The green transition represents a major thematic shift in global capital markets and has become a central concern for investors, regulators, and financial professionals. While previous research shows that analysts are increasingly considering ESG factors in their recommendations and forecasts (Ioannou and Serafeim, 2015;

Park, Yoon, and Zach, 2024; Roger, 2024), little is known about how they allocate their attention in response to this broader green transition trend.

Local EV adoption has several advantages as an empirical setting to address this gap. Of course, there are many possible cues of the green transition, and we do not argue, nor do we need, our cue to be mutually exclusive. However, our proxy for EV adoption, charging infrastructure roll-out, exhibits substantial and, from the perspective of an individual analyst, plausibly exogenous heterogeneity across MSAs (Figure 1) and over time (Figure 2), allowing us to exploit this variation to examine how local environmental cues influence analyst behavior. Further, EV adoption represents a visible example of the green transition and reflects a concrete realization of the green economy (Springel, 2021). We interpret this measure as capturing broader local green transition intensity, serving as a proxy for the local environmental context that may influence analysts' perceptions and priorities.

Ex ante, the effect of local EV adoption on analysts' attention allocation is theoretically ambiguous. Salient local cues of the green transition may induce analysts to strategically reallocate attention toward firms and issues they perceive as more important under the emerging green economy. Such reallocation may be broad, encompassing all ESG-sensitive firms, as analysts invest more effort in developing ESG-related knowledge across both positively exposed (green) and negatively exposed (brown) firms relative to firms less exposed to sustainability issues (Dhaliwal, Radhakrishnan, Tsang, and Yang, 2012). Alternatively, reallocation may be selective, with analysts devoting disproportionately greater effort to firms expected to benefit from green transition opportunities relative to firms facing adverse transition risks (Lim, 2001; Chen, Li, Ma, and Michaely, 2025).

To construct our measure of local EV adoption, we obtain granular data on the deployment

of public EV charging infrastructure from the US Department of Energy's Alternative Fuels Data Center. EV adoption[1] is proxied by the quarterly change in the number of public EV chargers per unit of land area, capturing the salience of local cues. Our final sample comprises 1,477 unique analysts across 52 MSAs, covering nearly 5,000 US public firms from 2015Q1 to 2020Q1. The sample period is chosen to capture the onset of widespread EV adoption in the US, as shown in Figure 2, while avoiding potential confounding effects from the COVID-19 pandemic. During this early expansionary phase, we focus on the growth in charger density to capture how a significant local surge in EV infrastructure shapes analyst forecasting behavior. We define green firms as those in the bottom 20% of Trucost Scope 1 carbon emission intensity (scaled by revenue) within their Fama-French 12 industry groups to establish a consistent classification of environmentally friendly firms across diverse industries for our analysis.

We first provide direct evidence of a shift in attention and effort allocation. We find that during periods of high local EV adoption, analysts exhibit a higher frequency of forecast revisions for green firms, suggesting increased monitoring and engagement. Moreover, impacted analysts who cover more green firms are more likely to raise climate-related questions during earnings conference calls, indicating greater effort to acquire climate-related information about those green firms. Additionally, we find that these analysts are significantly more likely to mention EV-related terms in their reports, and are also more inclined to use climate change-related bigrams more broadly. When decomposing these bigrams into thematic categories, we observe that the increase is concentrated in opportunity-oriented language—such as references to clean energy or renewable investment—rather than regulatory or physical risk terms. These findings suggest that local green

[1]Throughout this paper, we use the term "EV adoption" to refer to the deployment of EV charging infrastructure.

transition cues do not uniformly enhance analysts' forecasting capacity, but instead reallocate their attention and efforts toward opportunities for sustainability-aligned firms.

Next, we examine the outcome of this effort reallocation and find that local EV adoption significantly improves analysts' forecast accuracy for green firms relative to non-green firms. In terms of economic magnitude, an interquartile increase in local EV adoption is associated with a 3.30% reduction in forecast error for green firms relative to non-green firms when scaled by the full-sample mean, which is comparable to other factors affecting analyst forecast accuracy, such as industry experience (Bradley, Gokkaya, and Liu, 2017). Moreover, when we partition firms into three groups—green firms, brown firms, and environmentally neutral firms—we find that forecast accuracy improves only for green firms relative to neutral firms, while forecast accuracy for brown firms is not significantly different from that for neutral firms. This finding is inconsistent with the hypothesis that analysts reallocate attention toward ESG-related factors more broadly. Instead, it again supports the hypothesis that analysts selectively reallocate attention toward firms that are more likely to benefit from green transition opportunities, rather than toward firms primarily exposed to transition-related risks. Finally, we find that the accuracy improvement is greater among green firms with greater information asymmetry. This further suggests that analysts' selective attention adds more marginal value when applied to more opaque firms, where the informational environment is less transparent, and the marginal gain to additional analysis is higher. The predictable variation in the effect further strengthens our interpretation that we are observing attention reallocation that impacts a firm's information environment.

A natural question is whether, considering all firms covered by the analysts, heightened EV salience results in net improvement in forecast accuracy. If a net improvement were present, it would suggest that EV salience enhances analysts' general forecasting ability rather than operating

through a reallocation of limited attention toward green firms. However, our analysis yields no evidence of a net improvement. Instead, while forecast accuracy for green firms improves, forecast quality for non-green firms deteriorates modestly during periods of elevated EV adoption. This pattern is consistent with analysts reallocating their limited attention and effort toward green firms and away from non-green firms.

To mitigate concerns about potential endogeneity, we include three sets of high-dimensional fixed effects—firm $\times$ fiscal quarter, analyst $\times$ year-quarter, and analyst $\times$ firm fixed effects—to flexibly control for analyst-firm matching, as well as time-varying firm and analyst characteristics. These fixed effects together serve as a triple-difference design (Wooldridge, 2007). Our estimated effects come from comparing how the forecast accuracy gap between green and non-green firms varies over time for the same analyst, and further comparing this variation across analysts in different MSAs. This design helps rule out a wide range of confounding factors and alternative explanations. For example, the analyst $\times$ firm fixed effect alleviates concerns that certain analysts are systematically better at forecasting green firms for reasons unrelated to local EV adoption; the firm $\times$ fiscal quarter fixed effect alleviates concerns that the green firms become easier to forecast during high-EV salience period. Furthermore, local EV adoption is largely shaped by public infrastructure investments and automaker deployment strategies, making it plausibly exogenous to analysts' forecasting behavior.

Our findings are robust to a wide range of alternative specifications, measurement choices, and sample restrictions. The results remain similar when using the level of charging infrastructure instead of growth—consistent with our sample capturing the early phase of rapid EV expansion during which levels and growth evolve closely—and when scaling charger deployment by population. They are also robust to more stringent fixed effects, including MSA $\times$ year-quarter $\times$

green-firm fixed effects, as well as to controls for local economic conditions that may coincide with EV expansion. Finally, the results remain stable across a range of further checks—including excluding major regions or industries, suggesting that the findings are not driven by specific geographic or sectoral factors.

We further investigate the broader market and career implications of these findings. First, we examine whether improved forecast accuracy translates into more informative market signals. Stock prices react more strongly to forecast revisions of green firms' EPS made by analysts experiencing high EV salience, suggesting that investors recognize the value of their enhanced attention. Second, we find that green firms covered by analysts in high-EV-salience areas experience lower bid-ask spreads and reduced Amihud (2002) illiquidity, indicating measurable improvements in their information environment. Finally, we document important career benefits: analysts with superior green firm forecasting ability are more likely to become All-Star analysts in the following year, suggesting that this strategic effort reallocation is both market-relevant and personally rewarding.

Our study contributes to the literature in several ways. First, we contribute to research exploring how the allocation and constraints of analysts' cognitive resources affect forecast accuracy. Prior literature has documented various factors affecting analysts' information processing capacity: behavioral biases such as decision fatigue (Hirshleifer, Levi, Lourie, and Teoh, 2019) and attention-distracting events (Driskill, Kirk, and Tucker, 2020; Cuculiza, Antoniou, Kumar, and Maligkris, 2021; Bourveau, Garel, Joos, and Petit-Romec, 2024; Han, Mao, Tan, and Zhang, 2024), as well as strategic allocation of resources due to career concerns (Harford et al., 2019). Further, analysts often use *firm-specific* local information in forecasting, which can lead to either biased or more accurate earnings forecasts and increased coverage (Malloy, 2005; O'Brien and

Tan, 2015; Gerken and Painter, 2023). Our paper extends this literature by showing how broader salient cues of important trends shape analysts' effort allocation toward information production relevant to the emerging trend.

Second, our study contributes to the literature examining how exogenous events shape analysts' forecasting behavior. Prior literature documents how external shocks influence analysts' information production—including macroeconomic uncertainty (Bochkay and Joos, 2021), accounting standard enforcement (Hope, 2003), terrorist attacks (Cuculiza et al., 2021), litigation and regulation (Leung and Srinidhi, 2006; Howard and Sinha, 2020), and climate-related disasters (Bourveau and Law, 2021; Han et al., 2024). These studies primarily focus on exogenous events that are episodic, cyclical, or disruptive shocks, capturing temporary fluctuations or unexpected disruptions rather than long-term structural shifts. Our setting differs in that EV adoption serves as a salient cue of an emerging economic trend—a concrete, forward-looking manifestation of the green transition rather than a transitory macroeconomic fluctuation or a one-off negative event. This distinction is particularly relevant when contrasted with climate-related disasters and other adverse ESG events: whereas such events tend to heighten broad, risk-oriented awareness of sustainability issues, the expansion of local EV infrastructure captures the opportunity side of the green transition, directing analysts' attention toward firms positioned to benefit from structural changes in the economy.

Third, our study contributes to the growing literature on how analysts incorporate ESG information into their assessments. Prior research shows that analysts integrate ESG risks into their forecasts and recommendations, particularly following negative ESG events and material sustainability incidents (Derrien, Krueger, Landier, and Yao, 2024; Park et al., 2024), and address climate-related topics in earnings calls and reports (Chan, 2024; Sautner, van Lent, Vilkov, and Zhang, 2024).

However, existing literature primarily focuses on analysts' responses to explicit, firm-specific ESG information. We extend this by showing how ambient local environmental cues—specifically, the physical manifestation of green transitions through EV infrastructure—shape analysts' attention allocation and assessment of environmentally friendly firms, highlighting an unexplored channel through which environmental awareness influences fundamental analysis beyond direct ESG disclosures.

Taken together, our results reveal that the expansion of EV infrastructure—while primarily a transportation and environmental policy initiative—generates important spillover effects on financial markets through the information intermediaries' attention channel. By making the green transition more salient in analysts' local environments, EV development shapes how these key information intermediaries process information and allocate their limited cognitive resources. This reallocation of analytical effort toward sustainability-aligned firms indirectly improves capital market coverage and investor recognition, enhancing their information environment, reducing information asymmetry, and potentially improving green firms' access to financing.

II. HYPOTHESIS DEVELOPMENT

We examine whether salient local cues of broader economic trends alter analyst effort allocation and, in turn, affect the information environment. We answer this question in the context of how the salience of the green transition, captured through electric vehicle (EV) infrastructure expansion, shapes how analysts allocate attention across their covered firms. Under our null hypothesis, these contextual cues have no impact as analysts already utilize all available information. If an effect exists, it may differ between green and brown firms depending on how analysts respond to salient local cues.

Prior research establishes that analyst attention is a scarce cognitive resource allocated unevenly across covered firms. Analysts devote disproportionate effort to firms that are more consequential for their career outcomes (Harford et al., 2019), while attention-distracting events demonstrably degrade forecast quality for firms that fall outside analysts' immediate focus (Driskill et al., 2020; Bourveau et al., 2024). Local informational environments further shape this allocation: geographic proximity to covered firms affects both coverage decisions and forecast accuracy (Malloy, 2005; Gerken and Painter, 2023), suggesting that ambient contextual cues in analysts' surroundings can systematically redirect analytical focus. The expansion of EV infrastructure may function as precisely such a cue—yet unlike proximity to a covered firm, which confers informational advantages tied to a specific firm's local operations, the proliferation of charging stations in an analyst's own city represents a diffuse, non-firm-specific signal that elevates the perceived importance of sustainability-aligned firms broadly. We therefore posit that greater local EV salience induces analysts to strategically reallocate their attention and effort across the firms they cover.

H1: *Greater local EV salience leads analysts to strategically reallocate attention and effort toward firms perceived as more exposed to the green transition.*

Two distinct reallocation patterns may arise *ex ante*. First, EV salience may elevate the overall salience of sustainability as an analytical dimension, prompting analysts to broadly devote more effort to understanding sustainability-related risks and opportunities across firms (Dhaliwal et al., 2012). Under this scenario, analysts increase their analytical effort with both green and brown firms as sustainability considerations become more central to their valuation.

H1a: *Greater local EV salience increases analysts' effort devoted to both green and brown firms relative to firms with neutral environmental profiles.*

Second, analysts may selectively reallocate attention toward green firms in particular. Prior

literature suggests that analysts tend to focus more on the growth opportunities associated with the green transition rather than on the downside risks it poses (Chan, 2024; Sautner et al., 2024; Chen et al., 2025). Analysts may therefore perceive firms well-positioned to benefit from green transition opportunities as more deserving of incremental effort. At the same time, analysts may be reluctant to devote extra attention to brown firms, as doing so would require emphasizing potential downside risks—behavior inconsistent with career incentives that discourage analysts from highlighting negative information (Lim, 2001; Green, Hand, and Sikochi, 2024; Hirshleifer et al., 2024).

H1b: *Greater local EV salience selectively increases analysts' effort devoted to green firms relative to non-green firms.*

III. DATA, VARIABLE CONSTRUCTION, AND SUMMARY STATISTICS

A. Electric Vehicle Adoption

We measure local electric vehicle (EV) adoption using data on EV chargers, since charging stations play a key role in EV adoption (Springel, 2021; Rapson and Muehlegger, 2023). We collect detailed city-level public EV charging infrastructure from the US Department of Energy's Alternative Fuels Data Center (AFDC), which includes information on the number of chargers at each location, charger types, and whether the chargers are in operation. We aggregate the city-level EV charger data to the MSA level since MSAs better capture where analysts work and live.

To construct standardized EV salience measures for each MSA, we scale the change in the number of chargers by land area.[2] The EV salience measure is defined as follows,

[2] As robustness checks, we use population-scaled EV salience, log value of new EV chargers, and land-area-scaled cumulative count of EV chargers. Land area and population data are from the US Census Bureau.

$$EV\ Salience_{k,q} = \frac{\Delta EV\ Chargers_{k,q}}{Land\ Area_k},$$

where $\Delta EV\ Chargers_{k,q}$ denotes the change in the number of EV chargers in MSA k during quarter q.[3]

Figures 1 and 2 together illustrate the spatial and temporal variation in EV adoption. Figure 1 maps EV charger density across MSAs in the contiguous 48 US states in 2015Q1 and 2020Q1, while Figure 2 plots quarterly charger growth rates within the five MSAs with the largest cumulative expansion between 2010 and 2020. Beyond level differences across MSAs, Figure 2 reveals striking heterogeneity in adoption trajectories: charger installations in New York grow moderately around 2016–2017, whereas those near San Jose accelerate sharply in 2019–2020 as New York growth peaks. This joint spatiotemporal variation provides the identifying variation we exploit to study how local environmental cues shape analyst behavior. EV adoption accelerates noticeably after 2015,[4] which motivates our sample start date; we end the sample in 2020Q1 to avoid confounds from COVID-19.

To understand the factors driving EV adoption and assess our identification strategy's plausibility, we examine the determinants of EV salience in Appendix Table A.2. Panel A restricts the analysis to MSAs where analysts are located, while Panel B includes all US MSAs. Consis-

[3] We scale by land area rather than population because it better captures the physical visibility of EV infrastructure in analysts' daily environment, which is the mechanism central to our salience argument. We use the quarterly change in EV chargers rather than the cumulative level because marginal additions to local infrastructure represent novel informational cues that are more likely to capture analysts' attention, whereas the existing stock of chargers gradually recedes into the background and exerts diminishing attentional effects (Bordalo et al., 2012, 2013). Results remain quantitatively similar under alternative specifications using population scaling or the cumulative charger level (see Table A.3). The robustness to the level measure is unsurprising given that our sample spans the early expansion phase of EV adoption, during which growth and cumulative stock are strongly correlated.

[4] Several concurrent developments contributed to this acceleration: the 2015 Paris Climate Agreement, a sharp decline in lithium-ion battery costs, continued federal tax incentives of up to $7,500, shifting consumer perceptions following the 2012 Tesla Model S launch, and the introduction of more affordable models such as the Chevrolet Bolt during 2015–2017.

tent with prior studies (Union of Concerned Scientists and Consumer Reports, 2022; Davis, Li, and Springel, 2025), areas with higher Asian population shares and stronger Democratic leanings exhibit significantly greater EV infrastructure expansion in the full MSA sample. Beyond demographics and political preferences, energy prices (particularly gas prices), climate concern levels, EV-related policy environments, and commute times also significantly predict local EV salience.[5] Notably, analysts in our sample are concentrated in large metropolitan areas with predominantly Democratic-leaning populations. This concentration explains why the Democratic vote share variable loses statistical significance in the analyst sample (Panel A) versus the full MSA sample (Panel B).

Importantly, while these observable local characteristics explain a portion of EV salience variation, the adjusted R^2 in our analyst sample (Panel A, Column 5) is 42.7%, indicating substantial unexplained variation. Much of the residual variation likely stems from supply-side factors largely exogenous to analysts' forecasting behavior, including technical approval processes (land use permits, environmental assessments, grid connection authorizations), charger manufacturers' production capacity and installation schedules, and electrical infrastructure upgrades. These supply-side factors are unobservable to individual analysts, with quarter-to-quarter timing effectively unpredictable from any single analyst's perspective. This supports our identifying assumption that the precise timing of local EV infrastructure expansion represents plausibly exogenous variation in local environmental cues shaping analysts' attention allocation.

[5]Data sources for these local characteristics include: the US Census Bureau, the Bureau of Labor Statistics, the American Community Survey, the US Energy Information Administration, the Yale Program on Climate Change Communication, and the Alternative Fuels Data Center.

B. Analyst Data and Forecast Measures

We obtain quarterly earnings per share (EPS) forecasts from the *Institutional Brokers' Estimate System (I/B/E/S)* database. To avoid potential information leakage surrounding earnings announcements, we exclude forecasts issued within two calendar days prior to the earnings release. For each unique set of analyst, firm, and fiscal quarter, we retain only the analyst's most recent EPS forecast. We focus on one-quarter-ahead EPS forecasts, as our objective is to examine analysts' timely forecasting activities.

We merge the I/B/E/S forecast data with stock prices obtained from the Center for Research in Security Prices (CRSP) database to calculate forecast accuracy, which is inversely proxied by the forecast error. Specifically, the forecast error for analyst i's (in MSA k) forecast issued for firm j's earnings in quarter q is defined as:

$$Forecast\ Error_{i,j,k,q} = \left| \frac{\hat{EPS}_{i,j,k,q} - EPS_{j,q}}{P_{j,q^*}} \right|,$$

where $\hat{EPS}_{i,j,k,q}$ is analyst i's (in MSA k) most recent forecast of EPS issued in quarter q for firm j, $EPS_{j,q}$ is the actual EPS for firm j in quarter q, and P_{j,q^*} denotes firm j's stock price at the end of the prior calendar year relative to quarter q. To mitigate the influence of extreme values and improve the robustness of our results, we winsorize the forecast error at the 1% and 99% levels.

We also construct two measures of forecast revision frequency to capture analysts' effort level. Following Harford et al. (2019), *Relative Frequency* is defined as:

$$Relative\ Frequency_{i,j,q} = \#Revision_{i,j,q} - \overline{\#Revision}_{j,q},$$

where $\#Revision_{i,j,q}$ denotes the number of forecasts issued by analyst i for firm j in quarter q,

and $\overline{\#Revision}_{j,q}$ denotes the mean number of forecasts issued by all analysts covering firm j in the same quarter. *Scaled Frequency* further normalizes this difference by the cross-sectional mean (Bourveau et al., 2024):

$$Scaled\ Frequency_{i,j,q} = \frac{\#Revision_{i,j,q} - \overline{\#Revision}_{j,q}}{\overline{\#Revision}_{j,q}}.$$

We further measure analyst effort using two additional data sources. We obtain climate-related question data from Sautner et al. (2024) to capture analyst engagement during earnings conference calls, and collect textual data from the Mergent Investext database to construct report-level environmental language measures, with climate-related bigrams following Sautner, van Lent, Vilkov, and Zhang (2023). We describe the construction of these variables in detail in Section 4.

Finally, we merge these data with analyst-level data on location, gender, and college graduation year collected from LinkedIn. Using the analysts' geographic locations, we can link the analyst-level data to our MSA-level electric vehicle adoption data, allowing us to analyze how analysts' forecasting behavior responds to their corresponding local cues.

C. Green Firm Classification

To construct our key firm-level variable *Green Firm*, we utilize carbon emission data from Trucost, which provides firm-level estimates of greenhouse gas (GHG) emissions across three scopes. Scope 1 emissions represent direct GHG emissions from sources owned or controlled by the firm, such as emissions from fuel combustion in company-operated facilities or vehicles. Scope 2 emissions are indirect emissions from purchased energy consumption, while Scope 3 emissions include all other indirect value chain emissions. We focus on Scope 1 emissions because they are the most directly attributable to a firm's own operations.

To ensure our results capture firm-level greenness rather than industry-level environmental im-

pact—and considering that analysts typically specialize in specific industries—we define green firms within industries. Industry classifications are obtained from the Compustat database using SIC codes, which we map into Fama-French 12 (FF12) industry groups. We use FF12 industries to ensure sufficient firm counts within each group for reliable intra-industry comparisons.[6] Within each FF12 industry, we classify green firms as those in the bottom 20% in terms of Scope 1 emission intensity (scaled by revenue).[7] For robustness, we also construct alternative definitions using the bottom 33% emission thresholds.

D. Summary Statistics

Our final sample comprises 1,477 unique analysts located in 52 distinct MSAs, covering all major US financial centers, and collectively following 4,949 firms across diverse industries and market sizes. Table 1 Panel A presents geographical distributions of the analysts in our sample. Consistent with prior studies (Cuculiza et al., 2021; Gerken and Painter, 2023), analysts from the New York-Newark-Jersey City MSA (henceforth, New York) make up 56.9% of the entire analyst universe of the sample. Table 1 Panel B reports the descriptive statistics of our main variables, with formal definitions provided in Table A.1. The average forecast error is 1.79%, comparable with prior literature on analyst forecast performance (e.g., Chen et al., 2024; Li and Wang, 2024). The unconditional mean value of EV salience is 0.0055, indicating that, on average, an MSA adds approximately 5 new EV chargers per 1,000 square miles each quarter.[8] This corresponds

[6] In untabulated results, we also define green firms unconditionally across the full sample rather than within industry, and find that our main results remain robust.

[7] We acknowledge that Trucost's data are not perfect, but by focusing on Scope 1, and firms in the extreme quintiles, we should minimize the impact of any data errors.

[8] Whether this is a large or small amount is debatable, but it is worth emphasizing that the EV station deployment is not the signal per se, but is meant to proxy for broader salience of EV penetration along with environmental preferences and policy.

to around 27 new chargers per quarter in a typical MSA such as Los Angeles. The proportion of green firms in our sample is 24.8%, which aligns closely with our classification method—where green firms are defined as those in the bottom 20% of Scope 1 carbon emission intensity (scaled by revenue) within each Fama-French 12 industry group based on Trucost data—suggesting broad consistency between our sample and Trucost coverage.

IV. DO ANALYSTS ALLOCATE GREATER ATTENTION AND EFFORT TO GREEN FIRMS WHEN EXPERIENCING LOCAL EV SALIENCE?

We begin our empirical analysis by examining whether local EV salience induces analysts to reallocate attention and effort toward green firms. We measure analyst effort along three complementary dimensions: the frequency of earnings forecast revisions, climate-related engagement during earnings conference calls, and the incorporation of environmental themes in analyst reports. Together, these measures provide direct evidence of how analysts respond to locally salient environmental cues, before we turn to the performance implications of this effort reallocation in Section 5.

A. Forecast Revision Frequency

To assess analyst effort in terms of forecast updates, we examine whether analysts issue more frequent revisions to earnings forecasts for green firms in response to heightened local EV salience. Earnings forecast revision frequency is a widely used proxy for analyst effort in the literature (e.g., Harford et al., 2019; Bourveau et al., 2024), capturing the effort analysts allocate to firm-specific analysis in response to evolving information.

We measure forecast revision frequency using two alternative dependent variables: *Relative*

Frequency and *Scaled Frequency*. *Relative Frequency* measures the number of forecasts issued by analyst i for firm j in quarter q, minus the mean number of forecasts issued by all analysts covering firm j in the same quarter (Harford et al., 2019). *Scaled Frequency* standardizes this measure by the mean number of forecasts issued by all analysts for firm j in quarter q (Bourveau et al., 2024). We estimate the following regression:

$$Frequency_{i,j,k,q} = \beta_1 EV\ Salience_{k,q} \times Green\ Firm_{j,q} + \mathbf{FEs} + \varepsilon_{i,j,k,q}, \tag{1}$$

where $Frequency_{i,j,k,q}$ denotes either *Relative Frequency* or *Scaled Frequency* for analyst i in MSA k covering firm j in quarter q; $EV\ Salience_{k,q}$ is the quarterly change in EV chargers per unit land area in MSA k during quarter q; and $Green\ Firm_{j,q}$ is an indicator equal to one if firm j falls in the bottom quintile of Scope 1 carbon emission intensity within its Fama-French 12 industry in the relevant fiscal year. Both specifications include firm $\times$ fiscal-quarter and analyst $\times$ year-quarter fixed effects. A positive β_1 indicates that analysts devote greater forecasting effort to green firms relative to non-green firms during periods of elevated local EV salience. The inclusion of firm $\times$ fiscal-quarter fixed effects ensures that we are comparing different analysts' forecast revision frequency on the same firm in the same quarter, directly addressing the concern of unobserved firm heterogeneity driving the results.

Table 2 reports the results. The coefficient on $EV\ Salience \times Green\ Firm$ is significantly positive for both *Relative Frequency* and *Scaled Frequency*, indicating that higher local EV salience is associated with increased forecast update frequency for green firms relative to non-green firms.[9] Economically, an interquartile increase in local EV salience (from the 25th to the 75th percentile) results in 6.86% more frequent earnings forecasts for green firms relative to non-green firms in

[9] In untabulated results, we find no significant effect of EV salience on forecast revision frequency for brown firms. We discuss the differential effects on green and brown firms in detail in Section 5.

terms of relative frequency, and 7.31% in terms of scaled frequency.[10]

B. Analyst Engagement in Earnings Calls

To capture analysts' forecasting effort beyond forecast frequency, we examine their engagement in earnings calls using data on analysts' climate-related questions from Sautner et al. (2024). Earnings calls provide a meaningful proxy for analyst attention, as the questions they ask reflect the issues they prioritize. We estimate the following regression:

$$ClimateConv_{i,k,q} = \beta_1 EV\ Salience_{k,q} \times Green\ Ratio_{i,q} + \mathbf{FEs} + \varepsilon_{i,k,q}, \tag{2}$$

where $ClimateConv_{i,k,q}$ denotes one of three indicator variables capturing analyst i's climate-related engagement during earnings calls in quarter q: $I(ClimateConv)$, equal to one if the analyst raises at least one climate-related question; $I(ClimateValue)$, equal to one if the analyst raises at least one climate-related question concerning conventional firm value implications (e.g., earnings, cost, margins); and $I(ClimateValues)$, equal to one if the analyst raises at least one climate-related question concerning broader ESG-related values concepts (e.g., sustainability goals, green strategy). $Green\ Ratio_{i,q}$ is the proportion of green firms in analyst i's coverage portfolio in the current year, i.e., aggregating firm-level green status to the analyst-quarter level. All specifications include analyst $\times$ year and MSA $\times$ year-quarter fixed effects. A positive β_1 indicates that analysts with greater green firm coverage engage more actively with management on climate-related issues during earnings calls when local EV salience is high.

Table 3 presents the results. Column 1 shows that analysts with higher green coverage are significantly more likely to raise climate-related questions when local EV salience is high, confirming

[10] Interquartile range economic significance is calculated as $E_{\bar{y}}^{IQR} = |b(p75_x - p25_x)/\bar{y}|$, where b denotes the coefficient of independent variable x. Substituting the statistics into the equation, we get $((0.0085 - 0.0015) \times 1.0542/0.1075) \times 100\% = 6.86\%$ for relative frequency and $((0.0085 - 0.0015) \times 0.7095/0.0679) \times 100\% = 7.31\%$ for scaled frequency.

that analysts not only shift effort toward green firms, but also pay particular attention to climate-related issues. Columns 2 and 3 decompose climate-related questions into *ClimateValue* and *ClimateValues*. While both coefficients are positive and similar in magnitude, only the *ClimateValues* questions in Column 3 remain statistically significant. This pattern likely reflects that green strategy and sustainability goals are more relevant for green firms in our sample, whereas climate-related valuation concerns are more relevant for brown firms facing direct financial risks from regulation or stranded assets.

C. Textual Content of Analyst Reports

To further capture analysts' effort allocation, we examine the textual content of analyst reports using data from the Mergent Investext database. For each analyst, we create indicator variables indicating whether their published reports contain specific environmental keywords during our sample period.

We consider two categories of environmental terms. First, we include EV-specific bigrams ("electric vehicle(s)" and "charging station(s)") to directly capture engagement with EV adoption topics. Second, adapting the climate-related bigram framework from Sautner et al. (2023), we extract the top five climate-related bigrams overall and within each thematic category—opportunity (e.g., "clean energy," "new energy"), regulation (e.g., "carbon emission," "gas emission"), and physical risk (e.g., "global warm," "coastal area").[11] We estimate the following regression:

$$\textit{Report Content}_{i,k,q} = \beta_1 \, \textit{EV Salience}_{k,q} \times \textit{Green Ratio}_{i,q} + \mathbf{FEs} + \varepsilon_{i,k,q}, \tag{3}$$

where $\textit{Report Content}_{i,k,q}$ denotes one of six indicator variables capturing analyst i's use of en-

[11] Due to technical constraints of the Mergent Investext database, we identify whether each analyst issued at least one report containing any phrase from a given keyword group. The search process becomes prohibitively slow when the keyword group exceeds five terms, motivating our focus on the top five bigrams within each category.

vironmental language in reports during quarter q: *EV Bigram*, equal to one if the analyst mentions EV-specific terms; *CC Bigram*, equal to one if the analyst uses any climate-related bigram; *CC\EV Bigram*, equal to one if the analyst uses climate-related bigrams excluding EV-specific terms; CC^{Opp} *Bigram*, CC^{Reg} *Bigram*, and CC^{Phy} *Bigram*, equal to one if the analyst uses opportunity-, regulation-, and physical risk-oriented climate bigrams, respectively. All specifications include analyst $\times$ year and MSA $\times$ year-quarter fixed effects. A positive β_1 indicates that analysts with greater green firm exposure incorporate more environmental language in their reports when local EV salience is high.

Table 4 presents the results. Column 1 shows that analysts covering more green firms are significantly more likely to mention EV-specific terms during high-EV periods. Column 2 reveals a significant increase in broader climate-related language, which remains significant even after removing EV-specific phrases (Column 3), suggesting analysts engage with broader environmental themes beyond merely echoing local cues. Columns 4–6 decompose climate bigrams into three subcategories. Notably, the increased climate attention is concentrated in opportunity-oriented language (Column 4), with little to no increase in regulation-related or physical risk-related bigrams (Columns 5–6). This selective emphasis confirms that local EV salience—as a concrete manifestation of green transition opportunities—reallocates analyst attention toward opportunity-related narratives for green firms rather than the regulatory burden more relevant to brown firms.

Collectively, these three measures point to a consistent pattern: local EV salience prompts analysts to selectively allocate attention and effort to green firms. This reallocation is evident not only in analysts' forecasting activity, but also in how they engage with management and frame their written analysis—with a clear tilt toward climate opportunities rather than transition risks.

V. IMPACTS ON FORECAST ACCURACY

Having established that local EV salience shifts analysts' attention and effort toward green firms, we now examine whether this reallocation improves forecast accuracy. We first estimate the baseline effect, followed by cross-sectional heterogeneity due to information asymmetry of covered firms. We then test whether the accuracy gains reflect a net improvement or a reallocation of limited attention, and finally assess the robustness of these findings across alternative measures and samples.

A. EV Salience and Forecast Accuracy

In this section, we examine how local EV salience affects analyst forecast accuracy for green firms. To conduct the test, we estimate the following regression:

$$Forecast\ Error_{i,j,k,q} = \beta_1 EV\ Salience_{k,q} \times Green\ Firm_{j,q} + \mathbf{X}_{i,j,q} + \mathbf{FEs} + \varepsilon_{i,j,k,q}, \tag{4}$$

where $Forecast\ Error_{i,j,k,q}$ is the forecast error of analyst i in MSA k for firm j in quarter q, $EV\ Salience_{k,q}$ is the EV salience of MSA k in quarter q, and $Green\ Firm_{j,q}$ equals one if firm j's Trucost Scope 1 emission intensity (scaled by revenue) is in the lowest quintile within its FF12 industry for the relevant fiscal year, and zero otherwise. Given our granular fixed effects, $\mathbf{X}_{i,j,q}$ includes only *Forecast Age*, the natural logarithm of calendar days from the forecast to the earnings announcement date (Clement, 1999) (Table 1 reports raw days for interpretation ease). Standard errors are clustered at the MSA level. If EV salience shifts analysts' attention toward green firms, we expect a negative β_1, indicating improved forecast accuracy. [12]

Table 5 presents the regression results. Our variable of interest, $EV\ Salience \times Green\ Firm$,

[12] A competing prediction is that heightened EV salience induces analysts to overweight salient green transition signals at the expense of financial fundamentals (Bordalo et al., 2012), which would instead imply a positive β_1.

is negatively related to forecast error across all specifications. This indicates that local green-transition cues enhance forecast accuracy for green firms relative to other firms, consistent with the attention reallocation hypothesis (H1). Throughout the specifications, we include firm $\times$ quarter and MSA $\times$ quarter (or analyst $\times$ quarter fixed effects that subsume MSA $\times$ quarter) fixed effects. The firm $\times$ quarter fixed effect rules out the possibility that green firms become easier to forecast over time, such as through improvements in sustainability disclosures or broader analyst coverage. The MSA $\times$ quarter fixed effect absorbs regional shocks that may independently affect analyst forecasting—such as local labor market conditions, regional economic cycles, or variation in the concentration of institutional investors across metro areas. In Column 3, replacing MSA $\times$ quarter with analyst $\times$ quarter fixed effects further absorbs time-varying analyst characteristics, such as changes in workload or general forecasting ability, while subsuming any residual regional variation. In Column 4, we further add analyst $\times$ firm fixed effects to ensure that the results are not driven by certain analysts having a persistent informational advantage over the specific green firms they cover.

Economically, under the specification with the largest economic magnitude in Column 3, an interquartile increase in local EV salience (25th to 75th percentile) results in 3.30% more accurate forecasts for green firms relative to non-green firms when scaled by the full-sample mean forecast error,[13] and 5.67% more accurate forecasts when scaled by green firms' mean forecast error.[14] Using our most stringent specification, the associated economic magnitudes are 3.02% and 5.20%.[15] Compared with *Forecast Age* in Column 3, the effect of an interquartile increase in local

[13]Interquartile range economic significance is calculated as $E_{\bar{y}}^{IQR} = |b(p75_x - p25_x)/\bar{y}|$, where b denotes the coefficient of independent variable x. Substituting the statistics into the equation, we get ((0.0085-0.0015)$\times$0.0843/0.0179)$\times$100%=3.30%.

[14]The unconditional mean value of forecast error for green firms is 0.0104.

[15]Our economic magnitude is comparable to other factors affecting analyst forecast accuracy. For example, Bradley

EV salience is equivalent to having analysts forecast 54 days closer to earnings announcements at the median forecast age of 78 days.[16]

To examine whether EV salience affects forecast accuracy for high-emission firms, we construct a *Brown Firm* indicator equal to one if the firm's Trucost Scope 1 emission intensity belongs to the highest quintile within its FF12 industry for the relevant fiscal year, and zero otherwise. Column 5 shows that forecast errors for brown firms relative to other firms exhibit a modest increase, significant at the 10% level. However, when we simultaneously include both green and brown firm indicators in Column 6, the coefficient on $EV\ Salience \times Brown\ Firm$ becomes statistically insignificant, suggesting that analysts' forecast accuracy for brown firms is indistinguishable from that of neutral-emission firms. These patterns reveal that the forecast accuracy improvements are concentrated among green firms rather than brown firms.

This finding is inconsistent with H1a, which posits that EV salience induces broad ESG-related knowledge accumulation. If analysts generally integrated ESG information, forecast accuracy should improve for both green and brown firms. However, the absence of forecast improvement for brown firms indicates that analysts do not uniformly enhance ESG analysis across their coverage portfolio. This asymmetry instead supports H1b: because the salience shock captures EV adoption—a concrete manifestation of green transition opportunities—affected analysts shift attention toward opportunity-related narratives for green firms rather than the regulatory costs that are more relevant to brown firms, consistent with the findings of Chan (2024).

We further examine whether the forecast accuracy improvement for green firms comes at the

et al. (2017) report a 3.58% drop in forecast error for analysts with related industry experience; Gerken and Painter (2023) find local car count difference is associated with a 5.6% increase in forecast error in the retail industry.

[16] An interquartile increase in local EV salience is equivalent to having analysts make a forecast 24 days ($78 \times \exp[(0.0085-0.0015)\times(-0.0843)/0.0005]$) before earnings announcements when evaluating at the median, i.e., 54 days ($78-24$) closer to the earnings announcement day.

expense of non-green firms—consistent with attention reallocation—or reflects a net improvement in overall forecasting ability. To distinguish between these two possibilities, we estimate Equation 4 separately for green and non-green firms, and examine the sign and significance of *EV Salience* in each subsample as well as in the full sample. Table 6 presents results from separate regressions for the full sample (Columns 1-2), green firms (Columns 3-4), and non-green firms (Columns 5-6). For green firms, the coefficient on *EV Salience* is consistently negative and statistically significant at the 5% level or higher across specifications,[17] confirming that local EV salience improves forecast accuracy for environmentally friendly companies. In contrast, for non-green firms, we observe positive and statistically significant coefficients at the 10% level, indicating that forecast errors for these firms increase with greater EV salience. When examining the full sample, the coefficients on *EV Salience* are positive but statistically insignificant, suggesting no overall improvement in forecast accuracy across all firms. This pattern strongly indicates that analysts are reallocating their limited attention rather than achieving net improvements in forecasting ability, with local EV salience redirecting cognitive resources toward green firms at the expense of non-green firms.

We argue that the effect of EV salience on analyst forecast accuracy is plausibly causal for several reasons. First, our stringent specification controls for comprehensive fixed effects, eliminating time-invariant and time-varying confounding variables at the firm, MSA, and analyst levels, such as changes in disclosure environments, regional shocks, and forecasting skills. Second, substantial heterogeneity in EV salience changes across MSAs and over time mitigates selection bias concerns (e.g., analysts in environmentally progressive regions having persistently high climate

[17] Unlike Equation 4, we only include firm $\times$ fiscal-quarter fixed effects and either MSA or analyst fixed effects. Including MSA $\times$ quarter or analyst $\times$ quarter fixed effects would absorb the independent variable *EV Salience*.

concerns and superior accuracy), as our identification leverages within-analyst temporal variations in EV salience. Third, reverse causality is unlikely, as individual analyst behavior is unlikely to influence local EV infrastructure deployment, which is predominantly driven by EV manufacturer expansion and public infrastructure development.

To examine the persistence of these effects, we assess the long-run impact of EV salience on forecast accuracy by interacting *Green Firm* with leads of *EV Salience*. Figure 3 presents the estimated coefficients for the benchmark quarter (quarter 0) through five quarters ahead (quarter +5). The improvement in forecast accuracy for green firms is greatest in the benchmark quarter and gradually dissipates over time. By quarter +4, the effect becomes statistically indistinguishable from zero. This pattern suggests that while local EV salience improves near-term forecasting performance for green firms, its impact fades over time as other analysts gradually shift attention to green firms.

B. Heterogeneity: Information Asymmetry of Covered Firms

We next explore whether the effect of EV salience on forecast accuracy varies with firm-level information asymmetry. We posit that the beneficial effects of increased analyst attention due to local EV salience would be more pronounced for firms with high information asymmetry. While information-transparent firms already enjoy thorough market scrutiny, high information asymmetry firms receive less attention and have fewer information intermediaries, creating greater opportunities for attentive analysts to discover value-relevant information. Thus, when local EV salience directs analysts' cognitive resources toward green firms, this enhanced attention should yield greater forecast accuracy improvements for firms with significant information gaps.

To test this hypothesis, Table 7 presents subsample regression results using proxies that capture

both traditional information asymmetry and ESG-related transparency. We classify firms with the following characteristics as having high information asymmetry: low market cap (at or below the median of the Fama-French 12 industry in the previous quarter), low analyst coverage (at or below the median of the Fama-French 12 industry in the previous year), no CSR report, and no stakeholder engagement policy.[18] The results demonstrate a consistent pattern: the effect of EV salience on green firm forecast accuracy is concentrated among firms with high information asymmetry. For traditional measures, the coefficient on $EV\ Salience \times Green\ Firm$ is -0.2832 ($p < 0.01$) for small-cap firms versus -0.0017 (insignificant) for large-cap firms (Columns 1-2, F-test $p = 0.000$), and -0.2512 ($p < 0.10$) for low-coverage firms versus -0.0378 ($p < 0.05$) for high-coverage firms (Columns 3-4, F-test $p = 0.001$). ESG-related transparency measures reveal similar patterns: coefficients of -0.1519 ($p < 0.01$) versus 0.0049 (insignificant) for firms without versus with CSR reports (Columns 5-6, F-test $p = 0.000$), and -0.0977 ($p < 0.01$) versus 0.0025 (insignificant) for firms without versus with stakeholder engagement policies (Columns 7-8, F-test $p = 0.030$).

These findings support our interpretation that EV salience operates through an attention reallocation mechanism: the marginal value of redirected analyst effort is greatest for firms with the largest information asymmetry, consistent with prior literature (Hirshleifer et al., 2019; Bourveau et al., 2024).

[18] We obtain firms' disclosure status on CSR reports and stakeholder engagement from LSEG ESG Database.

C. Robustness

Alternative Measures and Samples

To ensure the validity of our results, we conduct a battery of robustness checks under alternative samples and measures. First, consistent with prior studies, analysts from New York comprise 56.9% of our sample (Cuculiza et al., 2021; Gerken and Painter, 2023). We exclude these analysts to alleviate concerns that New York-specific factors drive our results. Column 1 of Table A.3 shows the coefficient remains significant at the 1% level.[19]

Second, to mitigate selection bias, we restrict the sample to analysts who entered the workforce before 2003 (before Tesla's founding), ensuring their location choices were made before EV awareness existed. Our strategy leverages within-region temporal variations in EV salience as quasi-exogenous shocks, which are unlikely to correlate with analysts' initial location preferences. Results in Column 2 remain significantly negative at the 1% level. Moreover, analyst mobility is generally low (Park et al., 2024), making dynamic relocation in response to evolving local environmental conditions implausible.

Third, to address concerns that local EV salience affects firms' own behavior and subsequently influences analyst effort, we restrict the sample to cases where analysts and firms are in different MSAs, decoupling analysts' EV exposure from firms' green transition dynamics. Column 3 shows results remain robust at the 1% level.

Fourth, to ensure our results are not mechanically driven by direct EV industry exposure, we exclude firms in automobile-related industries (e.g., Motor and Generator Manufacturing, Tire and Tube Merchant Wholesalers, Passenger Car Leasing) as classified by their 6-digit NAICS codes.

[19] Figure 2 shows that California experiences the most dramatic growth in EV chargers. In untabulated results, we find our result still holds if we exclude analysts from MSAs in California.

Column 4 shows findings persist at the 1% level.

Finally, to check whether our results are sensitive to the construction of key variables, we use alternative EV salience measures (population-scaled, log value, cumulative count; Columns 5-7) and alternative green firm thresholds (33rd percentile; Column 8). Coefficients remain negative and significant at the 1% or 5% level across all specifications.

More Stringent Controls and Fixed Effects

Table A.4 addresses two distinct sources of potential confounding. Columns 2 and 4 saturate the model with MSA $\times$ year $\times$ green firm fixed effects. This triple interaction directly eliminates any time-varying, MSA-level force that disproportionately shifts forecast accuracy for green relative to non-green firms—for instance, a regional surge in ESG-oriented institutional demand or a local policy push that simultaneously spurs EV infrastructure buildout and draws analyst attention toward green firms. By absorbing these within-MSA-year differentials, identification comes exclusively from analyst-level variation in EV salience exposure within the same MSA-year-firm-type cell, a considerably tighter comparison group than prior specifications.[20] Columns 3 and 4 tackle a second concern: the observable MSA characteristics that Table A.2 shows to predict EV adoption—demographic composition, gas prices, EV policy count, and household infrastructure—may independently affect analysts' propensity to analyze green firms more carefully. Interacting each of these characteristics with the green firm indicator severs this alternative pathway, ensuring that the negative coefficient on $EV\ Salience \times Green\ Firm$ does not merely proxy for environmentally progressive local conditions. Across all four columns, the coefficient of EV Salience $\times$

[20] One residual channel that even this fixed effect cannot fully absorb is the local institutional investors' differential demand for green firm information at the MSA $\times$ year-quarter $\times$ green firm level. In untabulated tests, the effect concentrates among firms with lower institutional investors' average EV exposure, indicating that local institutional demand does not drive the results.

Green Firm remains negative and statistically significant, confirming that the result is robust to both time-varying regional confounds and the specific observable channels through which local environments shape EV adoption.

VI. ECONOMIC CONSEQUENCES

In this section, we examine the economic consequences of the improved forecasting for green firms due to analyst effort reallocation along three dimensions: market reactions to forecast revisions, improvements in green firms' information environment, and analyst career outcomes.

A. Market Reaction to Forecast Revisions

If EV salience induces analysts to produce more valuable information about green firms, markets should respond more strongly to their forecast revisions. We estimate the following regression:

$$\begin{aligned} CAR_{i,j,k,r,q} = {} & \beta_1 EV\ Salience_{k,q} \times Green\ Firm_{j,q} \times Forecast\ Revision_{i,j,k,r,q} \\ & + \beta_2 EV\ Salience_{k,q} \times Green\ Firm_{j,q} + \beta_3 EV\ Salience_{k,q} \times Forecast\ Revision_{i,j,k,r,q} \\ & + \beta_4 Green\ Firm_{j,q} \times Forecast\ Revision_{i,j,k,r,q} + \beta_5 Forecast\ Revision_{i,j,k,r,q} \\ & + \mathbf{X}_{i,j,r,q} + \mathbf{FEs} + \varepsilon_{i,j,k,r,q}, \end{aligned} \tag{5}$$

where $CAR_{i,j,k,r,q}$ is the [0, 3]-day cumulative abnormal return around analyst i's r-th forecast revision for firm j in quarter q, adjusted by CAPM or Fama-French 3 factors; $Forecast\ Revision_{i,j,k,r,q}$ is the change in analyst i's earnings forecast at the r-th revision event, normalized by the cross-sectional standard deviation of all forecasts for firm j in quarter q.

Table 8 reports the regression results. Consistent with prior studies (Gleason and Lee, 2003; Green, Jame, Markov, and Subasi, 2014; Hirshleifer et al., 2019), the coefficient for *Forecast Revision*

is positive and statistically significant, confirming that analyst forecast revisions contain novel information and the market responds to them. More importantly, the coefficient for *EV Salience* $\times$ *Green Firm* $\times$ *Forecast Revision* is positive and statistically significant at the 5% level for both specifications. These results indicate that the stock market reacts more strongly to forecast revisions on green firms issued by analysts experiencing high EV salience, recognizing the value of their enhanced attention and effort.

B. Effects on Firms' Information Environment

Next, we examine whether greater analyst coverage under high EV salience improves green firms' information environment. As Section 5.2 shows, EV salience primarily benefits green firms in poor information environments, leading us to expect their information asymmetry to decline. We estimate the following regression:

$$\begin{aligned} Information\ Asymmetry_{j,q} = \beta_1 EV\ Salience\ Exposure_{j,q} \times Green\ Firm_{j,q} \\ + \beta_2 EV\ Salience\ Exposure_{j,q} + \mathbf{X}_{j,q} + \mathbf{FEs} + \varepsilon_{j,q}, \end{aligned} \tag{6}$$

where $Information\ Asymmetry_{j,q}$ is proxied by bid-ask spread or Amihud (2002) illiquidity in quarter q; $EV\ Salience\ Exposure_{j,q}$ is firm j's exposure to EV salience through its covering analysts, calculated as the sum of new EV chargers in all analysts' MSAs in quarter q, scaled by total land area. Lower values of information asymmetry indicate better information environments, thus we expect $\beta_1 < 0$.[21] Following Bourveau et al. (2024), we control for an array of variables potentially affecting firms' information environment, such as the number of covering analysts, the firm's fundamentals, institutional holding, stock return, price, and volatility. We also include firm fixed effects and year-quarter fixed effects, and cluster the standard errors at the firm level.

[21] Following the prior literature, we drop observations with stock prices below \$5 in the regression of Amihud's illiquidity.

Table 9 presents the results. We find a negative and statistically significant coefficient on *EV Salience Exposure* × *Green Firm* across both measures of information asymmetry. This indicates that the enhanced attention and effort devoted by analysts in high EV salience regions translate into real economic benefits for green firms by reducing bid-ask spreads and illiquidity. In contrast, the coefficient on *EV Salience Exposure* alone is not statistically significant, confirming that these information environment improvements are specific to green firms rather than applying to all covered firms.

C. Analyst Career Outcomes

Finally, we examine whether analysts' improved forecasting performance for green firms affects their career outcomes during our sample period. Specifically, we estimate a logit regression of All-Star status (from Institutional Investor magazine) on forecast performance. We employ two complementary specifications. The first simultaneously includes average forecast errors for both green and non-green firms, conducting a horse-race test to assess whether superior green firm forecasting ability predicts career advancement while holding constant performance on non-green firms. The second constructs an indicator for whether an analyst's green firm accuracy exceeds their non-green firm accuracy, measuring their relative forecasting advantage on green firms. Both specifications control for current All-Star status, portfolio size, gender, age, and green firm coverage ratio.

Table 10 reports the results. Column 1 shows that analysts with lower forecast errors for green firms are significantly more likely to become All-Stars in the subsequent year. Column 2 shows that analysts demonstrating superior relative performance on green firms are also significantly more likely to achieve All-Star status. These findings indicate that green firm forecasting skill enhances

career outcomes, suggesting that the effort reallocation toward green firms driven by EV salience is both market-relevant and career-rewarding, likely because the sample period overlapped with increased institutional investor interest in green firms. Overall, EV salience functions as a cue of emerging trends rather than a distortion in analysts' focus.

VII. CONCLUSION

This study examines how salient local cues of broader economic transitions influence financial analysts' effort allocation and forecast accuracy. Using EV charging station deployment as a proxy for local green transition intensity, we find that analysts exposed to higher local EV adoption produce more frequent forecast revisions, engage more actively in climate-related discussions during earnings calls, and emphasize opportunity-oriented climate themes in their reports. These behavioral shifts translate into improved forecast accuracy for green firms relative to non-green firms, stemming from a reallocation of analysts' limited attention rather than a net enhancement in overall forecasting ability. These effects are stronger among green firms with higher information asymmetry, where the marginal value of analyst attention is greater. Taken together, the evidence supports a selective attention reallocation hypothesis.

Our findings illuminate important linkages between environmental technology deployment and capital market information production. Beyond their direct impact on transportation and emissions, investments in EV infrastructure generate informational spillover effects by reshaping how financial intermediaries allocate attention and process information, thereby enhancing information flows in capital markets. As policymakers worldwide develop frameworks for climate and sustainable finance, our study highlights how green infrastructure and technology adoption can facilitate the broader low-carbon transition through improved capital market information intermediation.

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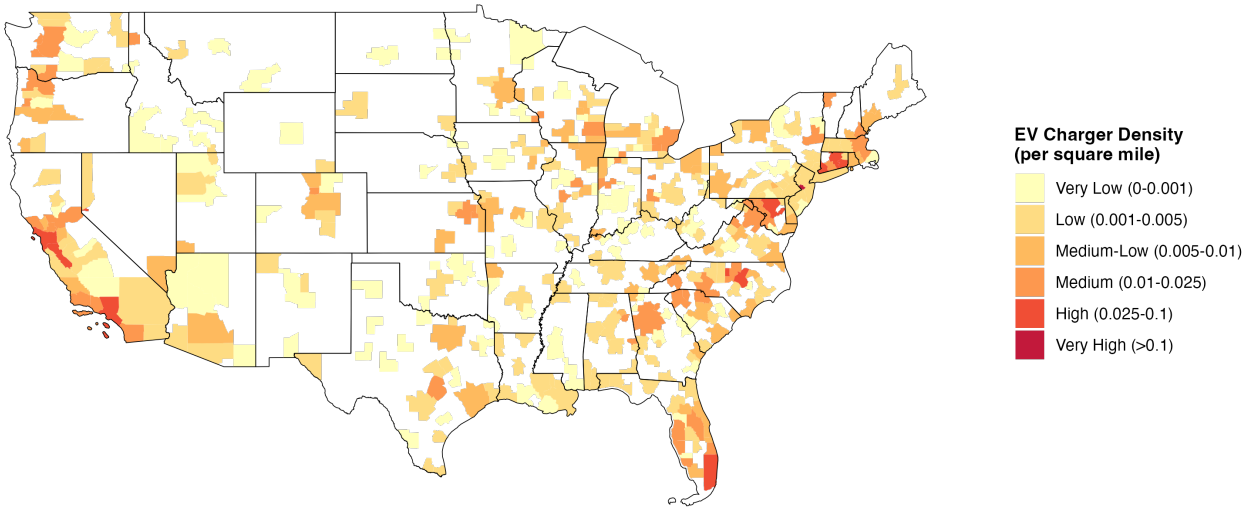
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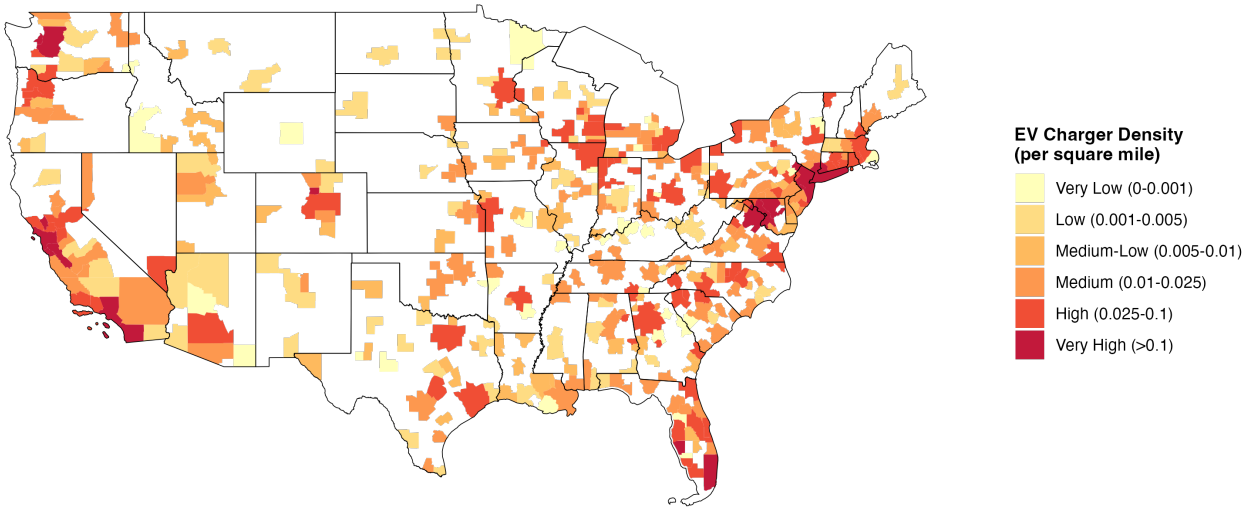
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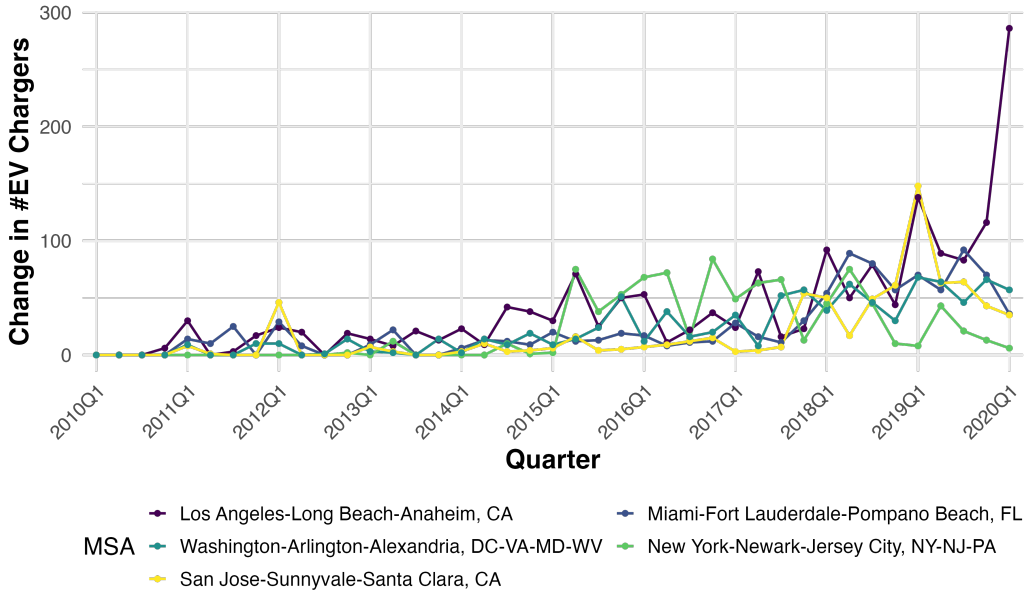
(a) EV Charger Density, 2015Q1



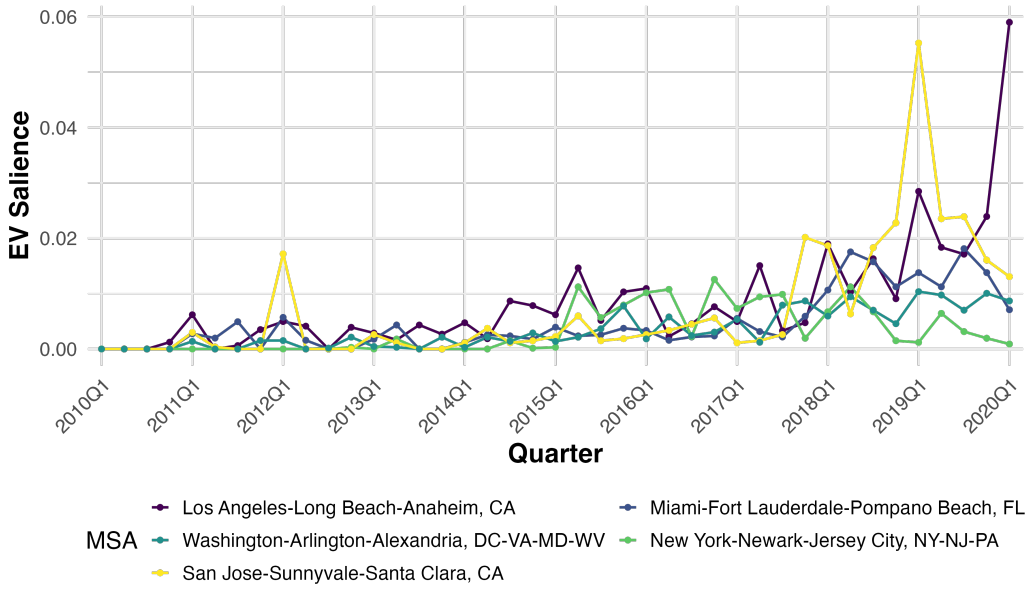
(b) EV Charger Density, 2020Q1

Figure 1. EV Charging Infrastructure Across MSAs: 2015Q1 vs. 2020Q1

This figure illustrates the geographical distribution of EV charging infrastructure across the United States. For each MSA, we calculate the EV charger density, defined as the number of chargers per square mile. Panels (a) and (b) display the MSA-level EV charger density in 2015Q1 and 2020Q1, respectively. The color gradient ranges from light yellow (Very Low: 0-0.001 chargers per square mile) to dark red (Very High: >0.1 chargers per square mile), with darker colors representing higher charger density.



(a) Change in #EV Chargers



(b) EV Salience

Figure 2. Growing Trend of EV Charging Infrastructures

This figure illustrates the quarterly growth in electric vehicle (EV) charging infrastructure across the five MSAs with the fastest cumulative expansion between 2010Q1 and 2020Q1. Panel (a) displays the absolute quarterly change in the number of EV chargers, while Panel (b) shows the EV salience measure (defined as the quarterly change in chargers normalized by MSA land area).

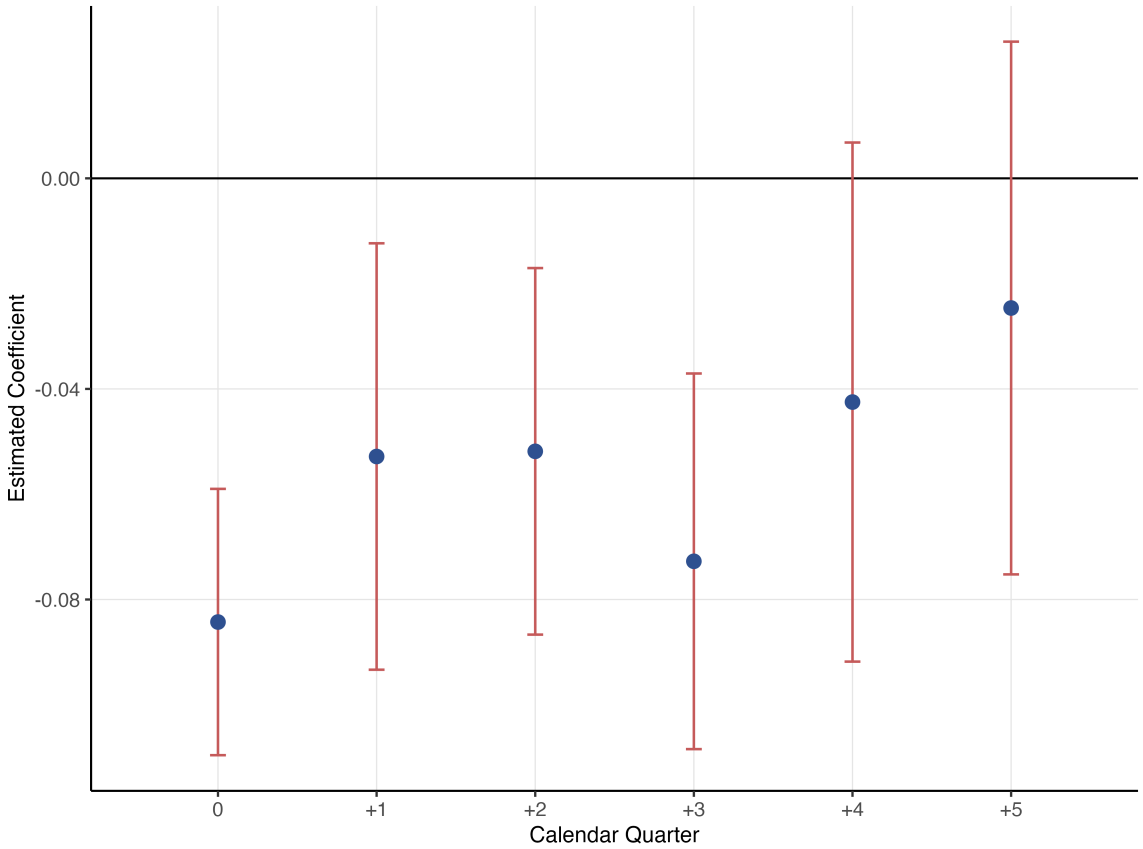


Figure 3. Long-Run Effects of EV Salience on Green Firm Forecast Accuracy

This figure plots the long-run effects of EV salience on green firm forecast accuracy. The dependent variable is *Forecast Error*. The figure displays coefficient estimates from regressions of *Forecast Error* on interactions between *Green Firm* and leads of *EV Salience*. Period 0 represents the baseline quarter. Blue dots represent estimated coefficients, and red bars represent 95% confidence intervals. The regressions include firm $\times$ fiscal-quarter, analyst $\times$ year-quarter fixed effects. Standard errors are clustered at the MSA level.

Table 1. Analyst Geographic Distribution and Summary Statistics

Panel A: Analyst Geographic Distribution by MSA

MSA	N	Percent
New York–Newark–Jersey City, NY–NJ–PA	835	56.88%
San Francisco–Oakland–Berkeley, CA	92	6.27%
Chicago–Naperville–Elgin, IL–IN–WI	64	4.36%
Boston–Cambridge–Newton, MA–NH	54	3.68%
Los Angeles–Long Beach–Anaheim, CA	39	2.66%
Minneapolis–St. Paul–Bloomington, MN–WI	38	2.59%
Houston–The Woodlands–Sugar Land, TX	33	2.25%
Cleveland–Elyria, OH	29	1.98%
Atlanta–Sandy Springs–Alpharetta, GA	27	1.84%
Portland–Vancouver–Hillsboro, OR–WA	26	1.77%
St. Louis, MO–IL	17	1.16%
Washington–Arlington–Alexandria, DC–VA–MD–WV	17	1.16%
Baltimore–Columbia–Towson, MD	16	1.09%
Little Rock–North Little Rock–Conway, AR	16	1.09%
Denver–Aurora–Lakewood, CO	15	1.02%
Dallas–Fort Worth–Arlington, TX	15	1.02%
Nashville–Davidson–Murfreesboro–Franklin, TN	15	1.02%
Miami–Fort Lauderdale–Pompano Beach, FL	14	0.95%
Philadelphia–Camden–Wilmington, PA–NJ–DE–MD	13	0.89%
Richmond, VA	11	0.75%
Others	82	5.59%

Panel B: Summary Statistics

Variable	N	Mean	SD	Q25	Median	Q75
Forecast Error	267,898	0.0179	0.1280	0.0005	0.0013	0.0035
EV Salience	267,898	0.0055	0.0059	0.0015	0.0033	0.0085
Green Firm	267,898	0.2484	0.4321	0.0000	0.0000	0.0000
Forecast Age (days)	267,898	63.7736	34.6355	28.0000	78.0000	91.0000
Relative Frequency	335,525	0.1075	0.6076	−0.2500	0.0000	0.5000
Scaled Frequency	335,525	0.0679	0.3618	−0.1818	0.0000	0.2941
$I(ClimateConv)$	20,206	0.3171	0.4654	0.0000	0.0000	1.0000
$I(ClimateValue)$	20,206	0.1731	0.3784	0.0000	0.0000	0.0000
$I(ClimateValues)$	20,206	0.0723	0.2589	0.0000	0.0000	0.0000
Bid-Ask Spread	43,645	0.0021	0.0066	0.0003	0.0006	0.0014
Amihud Illiquidity	41,150	0.0412	0.3147	0.0002	0.0007	0.0032

Panel A reports the geographic distribution of analysts across the top 20 Metropolitan Statistical Areas (MSAs). The table displays 20 of 52 total MSAs. Panel B presents summary statistics for key variables. The detailed definitions of these variables can be referred to in Table A.1.

Table 2. EV Salience and Forecast Revision Frequency

	(1) Relative Frequency	(2) Scaled Frequency
EV Salience × Green Firm	1.0542**	0.7095**
	(0.4836)	(0.2788)
Firm × Fiscal-Quarter FE	Yes	Yes
Analyst × Year-Quarter FE	Yes	Yes
N	335,525	335,525
Adj. R^2	0.242	0.218

This table reports the results for analyst forecast revision frequency. The regressions are estimated at the analyst-firm-quarter level. *Relative Frequency* is the number of forecasts issued by analyst i for firm j in quarter q minus the average number of forecasts issued by all analysts for firm j in quarter q. *Scaled Frequency* is the difference between the number of forecasts issued by analyst i for firm j in quarter q and the average number of forecasts issued by all analysts for firm j in quarter q, scaled by the average number of forecasts issued by all analysts for firm j in quarter q. *EV Salience* measures the salience of electric vehicles in each MSA and is calculated as the count of new EV charging stations divided by the land area of the MSA. *Green Firm* is an indicator equal to one if the firm is classified as a green firm, defined as having Trucost Scope 1 emission intensity (scaled by revenue) below the lowest quintile within its Fama-French 12 industry in a given fiscal year, and zero otherwise. Standard errors clustered at the MSA level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Analyst Conversation and Questions on Climate Issues

	(1) $I(ClimateConv)$	(2) $I(ClimateValue)$	(3) $I(ClimateValues)$
EV Salience × Green Ratio	5.2569**	2.0590	2.3064***
	(2.5360)	(1.7075)	(0.8066)
Analyst × Year FE	Yes	Yes	Yes
MSA × Year-Quarter FE	Yes	Yes	Yes
N	20,206	20,206	20,206
Adj. R^2	0.506	0.400	0.205

This table reports the results for the analyst's questions on climate issues. The regressions are at the analyst-quarter level. The data on analysts' climate questions are obtained from Sautner et al. (2024). $I(ClimateConv)$ is an indicator that equals 1 if the analyst asks at least one question that is classified as climate-related in a conversation in the earnings call in quarter q, and 0 otherwise. $I(ClimateValue)$ is an indicator that equals 1 if the analyst asks at least one question that is classified as climate-related and a *value* question (e.g. earnings, cost, margins) in a conversation in the earnings call in quarter q, and 0 otherwise. $I(ClimateValues)$ is an indicator that equals 1 if the analyst asks at least one question that is classified as climate-related and a *values* question (e.g. sustainability, goals, green strategy) in a conversation in the earnings call in quarter q, and 0 otherwise. *EV Salience* is the salience of electric vehicles in each MSA, calculated as the count of new EV charging stations divided by the land area of the MSA, and *Green Ratio* is the ratio of green firms in the portfolio of firms that an analyst covers, calculated as the count of green firms divided by the total number of firms that the analyst covers in that year. Standard errors clustered at the MSA level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Textual Content in Analyst Report

	EV Bigram	CC Bigram	CC\EV Bigram	CC^{Opp} Bigram	CC^{Reg} Bigram	CC^{Phy} Bigram
	(1)	(2)	(3)	(4)	(5)	(6)
EV Salience × Green Ratio	8.2840***	6.8076**	4.8431***	7.2213***	1.1897	1.6622***
	(1.3067)	(2.6042)	(1.7491)	(1.7068)	(4.4717)	(0.2935)
Analyst × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA × Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	12,486	12,486	12,486	12,486	12,486	12,486
Adj. R^2	0.539	0.533	0.487	0.539	0.383	0.096

This table reports the effect of EV salience on phrase usage in analyst reports. The regressions are at the analyst-quarter level. The dependent variable is an indicator that equals one if the analyst uses specific bigrams in reports in the next quarter, and zero otherwise. Column 1 examines EV Bigrams ("electric vehicle(s)", "charging station(s)"). Column 2 examines Climate Change (CC) Bigrams ("renewable energy", "electric vehicle(s)", "clean energy", "new energy", "climate change"). Column 3 examines CC Bigrams excluding "electric vehicle(s)" and "charging station(s)". Column 4 examines Opportunity-related Climate Change Bigrams ("renewable energy", "electric vehicle(s)", "clean energy", "new energy", "wind power"). Column 5 examines Regulatory Climate Change Bigrams ("greenhouse gas", "carbon emission", "gas emission", "carbon dioxide", "air pollution"). Column 6 examines Physical Climate Change Bigrams ("global warm", "coastal area", "electric bus", "snow ice", "forest land"). *EV Salience* is the salience of electric vehicles in each MSA, calculated as the count of new EV charging stations divided by the land area of the MSA, and *Green Ratio* is the ratio of green firms in the portfolio of firms that an analyst covers, calculated as the count of green firms divided by the total number of firms that the analyst covers in that year. Standard errors clustered at the MSA level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Forecast Error and EV Salience

	Forecast Error					
	(1)	(2)	(3)	(4)	(5)	(6)
EV Salience × Green Firm	-0.0618***	-0.0694***	-0.0843***	-0.0772***		-0.0767***
	(0.0186)	(0.0169)	(0.0127)	(0.0159)		(0.0156)
EV Salience × Brown Firm					0.0696*	0.0450
					(0.0377)	(0.0423)
Forecast Age	0.0006***	0.0007***	0.0005**	0.0005**	0.0005**	0.0005**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Firm × Fiscal-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA × Year-Quarter FE	Yes	Yes	No	No	No	No
Analyst FE	No	Yes	No	No	No	No
Analyst × Year-Quarter FE	No	No	Yes	Yes	Yes	Yes
Analyst × Firm FE	No	No	No	Yes	No	No
N	267,898	267,888	266,524	264,001	266,524	266,524
Adj. R^2	0.887	0.888	0.889	0.895	0.889	0.889

This table reports the results on how EV salience affects analysts' forecast accuracy. The regressions are at the forecast-analyst-firm-quarter level. The dependent variable is *Forecast Error*, defined as the absolute difference between the actual reported EPS and the analyst's forecasted EPS, scaled by the share price on the last trading day of the previous calendar year. The independent variable is *EV Salience* × *Green Firm*, where *EV Salience* is the salience of electric vehicles in each MSA, calculated as the count of new EV charging stations divided by the land area of the MSA, and *Green Firm* is an indicator that equals one if the firm is a green firm, i.e., its Trucost Scope 1 emission intensity (scaled by revenue) is below the lowest quintile within its Fama-French 12 industry for the relevant fiscal year, and zero otherwise. *Forecast Age* is the natural logarithm of the number of calendar days from the forecast to the earnings announcement date. Standard errors clustered at the MSA level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Does EV Salience Lead to Net Improvement in Forecast Accuracy?

	Forecast Error					
	Full Sample		Green Firms		Non-Green Firms	
	(1)	(2)	(3)	(4)	(5)	(6)
EV Salience	0.0178	0.0196	-0.0297***	-0.0290**	0.0372*	0.0411*
	(0.0126)	(0.0123)	(0.0106)	(0.0125)	(0.0201)	(0.0207)
Forecast Age	0.0004***	0.0004***	0.0001	0.0001	0.0005***	0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Firm × Fiscal-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	No	Yes	No	Yes	No
Analyst FE	No	Yes	No	Yes	No	Yes
N	267,921	267,911	66,539	66,504	201,381	201,365
Adj. R^2	0.887	0.888	0.920	0.920	0.881	0.882

This table reports the results on whether EV salience leads to net improvement in analyst forecast accuracy. The regressions are at the forecast-analyst-firm-quarter level. Columns 1-2 present results for the full sample, whereas Columns 3-4 and 5-6 report results for the green firm and non-green firm subsamples, respectively. The dependent variable is *Forecast Error*, defined as the absolute difference between the actual reported EPS and the analyst's forecasted EPS, scaled by the share price on the last trading day of the previous calendar year. The independent variable *EV Salience* is the salience of electric vehicles in each MSA, calculated as the count of new EV charging stations divided by the land area of the MSA. *Forecast Age* is the natural logarithm of the number of calendar days from the forecast to the earnings announcement date. Standard errors clustered at the MSA level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Information Asymmetry and Analyst Forecasts

	Forecast Error							
	Low Cap	High Cap	Low Cover	High Cover	No CSR Rpt	Have CSR Rpt	No Eng Pol	Have Eng Pol
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EV Salience × Green Firm	-0.2832***	-0.0017	-0.2512*	-0.0378**	-0.1519***	0.0049	-0.0977***	0.0025
	(0.0670)	(0.0126)	(0.1277)	(0.0142)	(0.0206)	(0.0058)	(0.0147)	(0.0036)
Forecast Age	0.0017*	0.0002	0.0012	0.0006**	0.0008***	0.0001	0.0008**	0.0000
	(0.0010)	(0.0001)	(0.0008)	(0.0002)	(0.0003)	(0.0001)	(0.0003)	(0.0000)
Firm × Fiscal-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	56,099	204,317	35,252	222,722	174,090	88,241	208,500	53,790
Adj. R^2	0.897	0.837	0.882	0.890	0.883	0.914	0.885	0.730
F-test (*p*-value)	0.000		0.001		0.000		0.030	

This table reports regression results of cross-firm heterogeneity in information asymmetry on analysts' forecast accuracy. The regressions are at the forecast-analyst-firm-quarter level. We classify whether a firm is information asymmetric based on its market capitalization (Column 1-2), analyst coverage (Column 3-4), CSR disclosure (Column 5-6), and stakeholder engagement (Column 7-8). Specifically, we classify firms with low market capitalization (at or below the median of the Fama-French 12 industry in the previous quarter), low total number of covering analysts (at or below the median of the Fama-French 12 industry in the previous year), no CSR report (no separate CSR report that year as indicated in LSEG ESG Database), and no stakeholder engagement policy (not disclosed in 10-K or CSR reports that year as indicated in LSEG ESG Database) as information asymmetric firms. The dependent variable is *Forecast Error*, defined as the absolute difference between the actual reported EPS and the analyst's forecasted EPS, scaled by the share price on the last trading day of the previous calendar year. The independent variable is *EV Salience* × *Green Firm*, where *EV Salience* is the salience of electric vehicles in each MSA, calculated as the count of new EV charging stations divided by the land area of the MSA, and *Green Firm* is an indicator that equals one if the firm is a green firm, i.e., its Trucost Scope 1 emission intensity (scaled by revenue) is below the lowest quintile within its Fama-French 12 industry for the relevant fiscal year, and zero otherwise. *Forecast Age* is the natural logarithm of the number of calendar days from the forecast to the earnings announcement date. Standard errors clustered at the MSA level are reported in parentheses. The last row presents the *p*-values of the *F*-test, which assesses whether the difference in the coefficient of *EV Salience* × *Green Firm* is statistically significant. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Stock Market Reaction to Analyst Forecast Revisions

	(1) $CAR^{CAPM}_{(0,3)}$	(2) $CAR^{FF3}_{(0,3)}$
EV Salience × Green Firm × Forecast Revision	0.1481**	0.1550**
	(0.0701)	(0.0674)
EV Salience × Green Firm	0.0511	0.0499
	(0.1521)	(0.1397)
EV Salience × Forecast Revision	0.0606	0.0564
	(0.0738)	(0.0713)
Green Firm × Forecast Revision	-0.0016**	-0.0017**
	(0.0007)	(0.0007)
Forecast Revision	0.0016***	0.0016***
	(0.0005)	(0.0005)
Forecast Age	-0.0000	0.0009**
	(0.0003)	(0.0004)
Firm × Fiscal-Quarter FE	Yes	Yes
Analyst × Year-Quarter FE	Yes	Yes
N	91,935	91,935
Adj. R^2	0.267	0.263

This table reports the regression results of market reaction to analyst forecast revisions. The regressions are at the forecast revision-analyst-firm-quarter level. The dependent variables $CAR^{CAPM}_{(0,3)}$ and $CAR^{FF3}_{(0,3)}$ are cumulative abnormal returns during the window of [0, 3] days of analyst forecast revision, adjusted by CAPM and Fama-French 3 factor model, respectively. *EV Salience* is the salience of electric vehicles in each MSA, calculated as the count of new EV charging stations divided by the land area of the MSA, and *Green Firm* is an indicator that equals one if the firm is a green firm, i.e., its Trucost Scope 1 emission intensity (scaled by revenue) is below the lowest quintile within its Fama-French 12 industry for the relevant fiscal year, and zero otherwise. *Forecast Revision* is the difference between analyst i's earnings forecast for firm j at the r-th revision event in quarter q and their immediately preceding forecast, normalized by the cross-sectional standard deviation of all analysts' forecasts for firm j in quarter q. *Forecast Age* is the natural logarithm of the number of calendar days from the forecast to the earnings announcement date. Standard errors clustered at the MSA level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9. Real Effects on Firms' Information Environment

	(1) Bid-Ask Spread	(2) Amihud Illiquidity
EV Salience Exposure × Green Firm	-0.0350**	-1.7406**
	(0.0164)	(0.8220)
EV Salience Exposure	0.0017	-0.2538
	(0.0123)	(0.4596)
Green Firm	0.0003*	-0.0070
	(0.0002)	(0.0095)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
N	43,645	41,150
Adj. R^2	0.718	0.699

This table reports the results of the real effects of EV salience exposure on firms' information environment. The regressions are at the firm-quarter level. $Bid-Ask\ Spread$ is the quarterly average of daily bid-ask spread measure, calculated as $100 \times (ask-bid)/[(ask+bid)/2]$, using daily closing bid and ask prices. *Amihud Illiquidity* is Amihud's (2002) illiquidity measure, defined as the quarterly average of daily $1,000,000 \times |ret|/(prc \times vol)$ in each quarter. *EV Salience Exposure* denotes the firm's exposure to the effect of EV salience through analysts covering the firm, calculated as the sum of newly established EV chargers in a given quarter in all the MSAs of analysts covering the firm in the year, scaled by the sum of land area of the corresponding MSAs. *Green Firm* is an indicator that equals one if the firm is a green firm, i.e., its Trucost Scope 1 emission intensity (scaled by revenue) is below the lowest quintile within its Fama-French 12 industry for the relevant fiscal year, and zero otherwise. Control variables include #analyst (natural logarithm of number of analysts plus one covering the firm in a given year), size (natural logarithm of firm's market cap), trading volume (natural logarithm of firm's annual trading volume scaled by 1,000), institutional holdings (percentage of a firm's equity held by all institutions), book-to-market ratio (ratio of book equity to market equity), leverage (ratio of total liabilities to the sum of total liabilities and common equity), return on assets (income before extraordinary items divided by total assets), price (natural logarithm of the stock price in the last trading day of the year), stock return (yearly buy-and-hold returns), and volatility (standard deviation of stock returns over the year). All control variables are lagged by one year. Standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10. Career Outcomes

	All-Star	
	(1)	(2)
Forecast Error (Green Firms)	-0.0722***	
	(0.0262)	
Forecast Error (Non-Green Firms)	-0.0192	
	(0.0178)	
Green Outperformance		0.2400***
		(0.0751)
Lag (All-Star)	5.1273***	5.1550***
	(0.1858)	(0.1852)
Number of Firms Covered	0.0616***	0.0588***
	(0.0036)	(0.0039)
Male	-0.2531***	-0.2326**
	(0.0945)	(0.1077)
Age	-0.0153***	-0.0143***
	(0.0034)	(0.0038)
Green Ratio	0.5884**	0.6157***
	(0.2569)	(0.2066)
Year FE	Yes	Yes
N	4,619	4,619
Pseudo R^2	0.582	0.580

This table presents logistic regression results for the effect of analysts' green firm forecasting capability on their career outcomes. The regressions are estimated at the analyst-year level. The dependent variable, *All-Star*, is an indicator equal to one if the analyst becomes an All-Star analyst in the following year. The variables of interest measure analysts' forecasting performance on green firms. Column 1 includes separate average forecast error measures for green and non-green firms, where lower values indicate better forecast accuracy. Column 2 uses an indicator, *Green Outperformance*, which is equal to one if the analyst's average forecast accuracy on green firms exceeds their accuracy on non-green firms in the given year. All specifications include year fixed effects and control for the all-star status, number of firms covered, analyst gender, age, and the percentage of green firms in the analyst's coverage portfolio in the current year. Standard errors in parentheses are clustered at the MSA level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix for
Salient Cues of Economic Transitions in Analyst Forecasting: Evidence from the Electric Vehicle Era

Xueqing Geng, Jarrad Harford, Frank Weikai Li, and Yonghao Archaelake Zhai

July 23, 2026

Table A.1. Variables and Definitions

Variables	Definitions
All-Star	An indicator that equals one if the analyst is listed an All-Star analyst in the October issue of Institutional Investor magazine.
Amihud Illiquidity	Amihud's illiquidity measure, defined as the quarterly average of daily $1,000,000 \times \lvert ret \rvert / (prc \times vol)$ in each quarter.
Bid-Ask Spread	The quarterly average of daily bid-ask spread measure, calculated as $100 \times (ask - bid)/[(ask + bid)/2]$, using daily closing bid and ask prices.
EV Salience	The salience of electric vehicles in each MSA, calculated as the count of new EV chargers divided by the land area of the MSA (per square mile).
EV Salience Exposure	The firm's exposure to the effect of EV salience through analysts covering the firm, calculated as the sum of newly established EV chargers in a given quarter in all the MSAs of analysts covering the firm in the year, scaled by the sum of land area of the corresponding MSAs.
Forecast Age	The natural logarithm of the number of calendar days from the forecast to the earnings announcement date.
Forecast Error	The absolute difference between the actual reported EPS and the analyst's forecasted EPS, scaled by the share price on the last trading day of the previous calendar year.
Forecast Revision	The difference between analyst i's earnings forecast for firm j at the r-th revision event in quarter q and their immediately preceding forecast, normalized by the cross-sectional standard deviation of all analysts' forecasts for firm j in quarter q.
Green Firm	An indicator that equals one if the firm is a green firm, i.e., its Trucost Scope 1 emission intensity (scaled by revenue) is below the lowest quintile within its Fama-French 12 industry for the relevant fiscal year, and zero otherwise.
Green Outperformance	An indicator that equals one if the analyst i 's average forecast accuracy on green firms exceeds their accuracy on non-green firms in the given year.
Green Ratio	The ratio of green firms in the portfolio of firms that an analyst covers, calculated as the count of green firms divided by the total number of firms that the analyst covers in that year.
$I(ClimateConv)$	An indicator that equals 1 if the analyst asks at least one question that is classified as climate-related in a conversation in the earnings call in quarter q, and 0 otherwise (Sautner et al., 2024).

Continued on next page

Table A.1 Continued from previous page

Variables	Definitions
$I(ClimateValue)$	An indicator that equals 1 if the analyst asks at least one question that is classified as climate-related and a *value* question in a conversation in the earnings call in quarter q, and 0 otherwise (Sautner et al., 2024).
$I(ClimateValues)$	An indicator that equals 1 if the analyst asks at least one question that is classified as climate-related and a *values* question in a conversation in the earnings call in quarter q, and 0 otherwise (Sautner et al., 2024).
No CSR Report	No separate CSR report that year as indicated in LSEG ESG Database.
No Engagement Policy	No stakeholder engagement policy is disclosed in 10-K or CSR reports that year as indicated in LSEG ESG Database.
Relative Frequency	The number of forecasts issued by analyst i for firm j in quarter q minus the mean number of forecasts issued by all analysts for firm j in quarter q.
Scaled Frequency	The number of forecasts issued by analyst i for firm j in quarter q minus the mean number of forecasts issued by all analysts for firm j in quarter q, scaled by the mean number of forecasts issued by all analysts for firm j in quarter q.

Table A.2. Determinants of EV Salience

Panel A: Analyst MSAs					
	EV Salience				
	(1)	(2)	(3)	(4)	(5)
Population Growth (%)	-0.4201***				-0.0865
	(0.1534)				(0.0778)
GDP Growth (%)	0.0088				-0.0027
	(0.0123)				(0.0161)
Income Growth (%)	0.0761**				0.0262
	(0.0308)				(0.0169)
Unemployment Rate (%)	-0.1043*				-0.0788
	(0.0541)				(0.0600)
Democratic (%)		0.0095			-0.0122
		(0.0084)			(0.0104)
Log(Age)		4.2438			2.3220
		(5.8049)			(4.5179)
Hispanic (%)		0.0362			-0.0378
		(0.1324)			(0.1135)
Black (%)		-0.1650			-0.1471*
		(0.1077)			(0.0800)
Asian (%)		0.8059***			0.4122***
		(0.1292)			(0.1179)
Male (%)		0.1476			-0.0613
		(0.2953)			(0.3178)
Bachelor (%)		0.0495			-0.0255
		(0.0742)			(0.0740)
Electricity Price			0.0054		-0.0024
			(0.0236)		(0.0242)
Gas Price			0.7014**		0.4927*
			(0.2904)		(0.2637)
Worried (%)			0.0111		-0.0160
			(0.0221)		(0.0131)
# EV Policy			0.0489***		0.0272**
			(0.0159)		(0.0116)
Family Size				1.8726	2.8220*
				(1.3363)	(1.5040)
Log(Commute Time)				14.5959***	3.9888*
				(2.9938)	(2.0029)
No Vehicle (%)				0.0426	-0.0113
				(0.1251)	(0.1281)
Detached Unit (%)				-0.0522	0.0178
				(0.1013)	(0.0884)
MSA FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
N	1,092	1,092	1,092	1,092	1,092
Adj. R^2	0.364	0.395	0.397	0.392	0.427

Panel B: All U.S. MSAs					
Dep Var	EV Salience				
	(1)	(2)	(3)	(4)	(5)
Population Growth (%)	-0.0380**				-0.0127
	(0.0157)				(0.0085)
GDP Growth (%)	0.0011				0.0008
	(0.0011)				(0.0011)
Income Growth (%)	0.0064**				-0.0011
	(0.0031)				(0.0022)
Unemployment Rate (%)	-0.0124*				-0.0075
	(0.0065)				(0.0068)
Democratic (%)		0.0072***			0.0046**
		(0.0025)			(0.0019)
Log(Age)		-0.7310			-0.9519
		(0.7360)			(0.7869)
Hispanic (%)		-0.0240			-0.0595**
		(0.0236)			(0.0293)
Black (%)		-0.0258			-0.0193
		(0.0178)			(0.0146)
Asian (%)		0.1989**			0.1555**
		(0.0967)			(0.0736)
Male (%)		0.0183			0.0573
		(0.0391)			(0.0372)
Bachelor (%)		0.0257**			0.0276**
		(0.0122)			(0.0117)
Electricity Price			0.0081		0.0042
			(0.0080)		(0.0079)
Gas Price			0.1212		0.1174*
			(0.0736)		(0.0707)
Worried (%)			0.0045*		0.0029
			(0.0026)		(0.0021)
# EV Policy			0.0146**		0.0130**
			(0.0057)		(0.0051)
Family Size				-0.0175	-0.0607
				(0.1217)	(0.1175)
Log(Commute Time)				1.9406***	1.4590***
				(0.5857)	(0.3486)
No Vehicle (%)				-0.0019	0.0145
				(0.0119)	(0.0121)
Detached Unit (%)				-0.0221**	-0.0050
				(0.0104)	(0.0086)
MSA FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
N	7,800	7,788	7,854	7,809	7,779
Adj. R^2	0.231	0.242	0.241	0.236	0.256

This table reports the results on the determinants of EV salience across different MSAs. Panel A restricts the sample to MSAs where analysts are located, while Panel B includes all US MSAs. The regressions are at the MSA-quarter level. The dependent variable is *EV Salience*, calculated as the count of new EV charging stations divided by the land area of MSAs. Column 1 includes MSA-level economic variables (population growth, GDP growth, income growth, and unemployment rate). Column 2 includes demographic characteristics (Democratic vote share, median age, racial composition, gender composition, and education level). Column 3 includes energy prices (electricity and gas prices), environmental attitudes (Worried, the percentage of residents worried about climate change), and policy environment (# EV Policy, the cumulative count of state-level EV-related policies). Column 4 includes household and infrastructure characteristics (family size, commute time, vehicle ownership, and housing structure). Column 5 includes all variables from Columns 1 through 4. All growth rates are year-over-year changes. All specifications include MSA and year-quarter fixed effects. Standard errors clustered at the MSA level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.3. Robustness Check: Alternative Measures and Samples

	Forecast Error							
	No NY MSA	Grad. Before 2003	Diff MSA	No Auto Ind	Full Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EV Salience × Green Firm	-0.0726***	-0.0698***	-0.0969***	-0.0842***				
	(0.0218)	(0.0196)	(0.0156)	(0.0132)				
EV Salience (Pop) × Green Firm					-0.0001***			
					(0.0000)			
Log(Δ EV) × Green Firm						-0.0002**		
						(0.0001)		
EV Salience (Cum) × Green Firm							-0.0085**	
							(0.0034)	
EV Salience × Green Firm (33%)								-0.0913***
								(0.0245)
Forecast Age	0.0005	0.0009***	0.0005**	0.0005**	0.0005**	0.0005**	0.0005**	0.0005**
	(0.0006)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Firm × Fiscal-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	108,444	180,365	240,916	258,195	266,524	266,524	266,524	266,524
Adj. R^2	0.875	0.887	0.887	0.888	0.889	0.889	0.889	0.889

This table reports robustness check results of EV salience on analyst forecast accuracy using alternative measures and samples. Column 1 excludes analysts residing in the New York-Newark-Jersey City MSA. Column 2 keeps only analysts who graduated before 2003 (Tesla's inception year). Column 3 restricts the sample to cases where analysts and firms are located in different MSAs. Column 4 drops firms from automobile-related industries (e.g., Motor and Generator Manufacturing, Tire and Tube Merchant Wholesalers, Passenger Car Leasing, etc., as decided by firms' 6-digit NAICS). Columns 5 to 7 use alternative EV salience measures. Specifically, in Column 5 we change the denominator of EV salience to MSA population, in Column 6 we use the natural logarithm of the count of newly established EV chargers in the MSA, in Column 7 we use the cumulative count of established EV chargers in the MSA, scaled by the land area of MSAs. In Column 8, we use a 33% threshold to define green firms. *Forecast Age* is the natural logarithm of the number of calendar days from the forecast to the earnings announcement date. Standard errors clustered at the MSA level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.4. Forecast Error and EV Salience under Stringent Controls and Fixed Effects

	Forecast Error			
	(1)	(2)	(3)	(4)
EV Salience × Green Firm	-0.0772***	-0.0553**	-0.0740***	-0.0521*
	(0.0159)	(0.0212)	(0.0228)	(0.0262)
Black (%) × Green Firm			-0.0000	
			(0.0001)	
Asian (%) × Green Firm			-0.0000	
			(0.0001)	
Gas Price × Green Firm			-0.0001	0.0001
			(0.0010)	(0.0011)
# EV Policy × Green Firm			-0.0000	-0.0002
			(0.0000)	(0.0002)
Family Size × Green Firm			0.0001	
			(0.0042)	
Log(Commute Time) × Green Firm			0.0015	
			(0.0034)	
Forecast Age	0.0005**	0.0005**	0.0005**	0.0005**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Firm × Fiscal-Quarter FE	Yes	Yes	Yes	Yes
Analyst × Year-Quarter FE	Yes	Yes	Yes	Yes
Analyst × Firm FE	Yes	Yes	Yes	Yes
MSA × Year × Green Firm FE	No	Yes	No	Yes
N	264,001	263,997	264,001	263,997
Adj. R^2	0.895	0.895	0.895	0.895

This table reports the results on how EV salience affects analysts' forecast accuracy under stringent controls and fixed effects. The regressions are at the forecast-analyst-firm-quarter level. The dependent variable is Forecast Error, defined as the absolute difference between the actual reported EPS and the analyst's forecasted EPS, scaled by the share price on the last trading day of the previous calendar year. The key independent variable is *EV Salience* × *Green Firm*, where *EV Salience* is the salience of electric vehicles in each MSA, calculated as the count of new EV charging stations divided by the land area of MSAs, and *Green Firm* is an indicator that equals one if the firm is a green firm (i.e., its Trucost Scope 1 emission intensity scaled by revenue is below the lowest quintile within its Fama-French 12 industry for the relevant fiscal year), and zero otherwise. Column 1 includes the baseline specification with Forecast Age. Columns 3 and 4 add interaction terms between *Green Firm* and MSA-level characteristics (demographic composition, energy prices, policy environment, and household/infrastructure characteristics) to control for potential confounding factors. All specifications include firm × fiscal-quarter, analyst × year-quarter, analyst × firm fixed effects, and Columns 2 and 4 further include MSA × year × green firm fixed effects. Standard errors clustered at the MSA level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.