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

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Abstract

We examine how salient cues of broad economic trends shape financial analysts' forecasting, using US MSA-level electric vehicle (EV) adoption as a proxy for local green salience. After controlling for MSA, analyst, and firm characteristics, analysts in high-EV areas make more accurate forecasts for green firms. This improvement reflects not a net gain in forecasting ability, but a reallocation of limited attention and effort toward green firms. The effect is stronger among male, younger, and less busy analysts, and for harder-to-value firms, and is accompanied by more frequent forecast revisions, greater climate-related engagement during earnings calls, and increased use of opportunity-oriented climate language in analyst reports. Markets respond more strongly to forecast revisions by these analysts, and the information environment of green firms improves under their coverage.

Keywords: Financial analysts; electric vehicles; local cues; limited attention; effort allocation; green firms
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1. 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 et al., 2019). This literature views effort allocation primarily as a function of firm characteristics.

In this study, we propose a new perspective: 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. For instance, the rise of new technologies, shifting consumer preferences, and increasing awareness of ESG issues may all heighten the salience of certain themes in the minds of analysts, altering how they prioritize their attention and analytical capacity across covered firms. These contextual developments can act as ambient cues that frame how analysts perceive the strategic value of firms.

We explore this perspective by examining how local electric vehicle (EV) adoption—used as a proxy for 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 et al., 2024; Roger, 2024), little is known about how they allocate their attention in response to this green transition trend. To be clear, while our identification strategy focuses on EV salience, we assume that it captures broader local green transition intensity—such as regional climate policy or public awareness. In this sense, EV adoption serves as a proxy for the local environmental context that may influence analysts' perceptions and priorities.

We choose the EV setting because the adoption of EV represents a visible example of the broader green transition and reflects the concrete realization of the green economy through real products, industries, and market activities (Springel, 2021).Importantly, compared with the risks associated with climate change—ranging from stringent environmental regulations to physical climate hazards—analysts place greater emphasis on the opportunity side of the transition, particularly the emerging prospects in the EV industry (Chan, 2024; Chen et al., 2025; Sautner et al., 2024). In addition, EV adoption exhibits substantial heterogeneity both across metropolitan statistical areas (MSAs) and over time within the same MSA, allowing us to exploit this variation to examine how local green salience influences analyst behavior (as shown in Figure 1 and Figure 2).

Ex ante, the effect of local EV adoption on analysts' forecasting is theoretically ambiguous. On the one hand, salient local cues of the green transition may induce analysts to strategically reallocate attention toward firms and issues perceived as more important (Harford et al., 2019). Such reallocation may be broad-based, as analysts invest more effort in developing ESG-related knowledge, thereby improving forecast accuracy for ESG-sensitive firms, including both green and brown firms, relative to firms less exposed to sustainability issues (Dhaliwal et al., 2012). Alternatively, attention reallocation may be selective, with analysts devoting greater effort to firms expected to benefit from green transition opportunities while avoiding deeper analysis of firms facing adverse transition risks (Chen et al., 2025; Lim, 2001), leading to higher forecast accuracy for green firms relative to non-green firms. On the other hand, because EV adoption is a vivid and symbolically powerful signal, it may induce salience-driven overreaction (Bordalo et al., 2012), leading analysts to overweight ESG-related information, inflate forecasts for green firms, become overly pessimistic about brown firms, and reduce forecast accuracy overall.

To construct our measure of local EV adoption, we use EV charger data 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 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. Forecast accuracy is computed from one-quarter-ahead EPS forecasts in the I/B/E/S database and stock price data from CRSP. 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 find that local EV adoption significantly improves analysts' forecast accuracy for

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

green firms relative to non-green firms. In terms of economic magnitude, an interquartile increase in local EV adoption is associated with 3.30% reductions 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 like industry experience (Bradley et al., 2017). This finding is consistent with the strategic attention reallocation hypothesis rather than the salience-driven overreaction hypothesis. 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 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.

To mitigate concerns about potential endogeneity, we include three sets of high-dimensional fixed effects—firm × fiscal quarter, analyst × year-quarter, and analyst × firm fixed effects—to flexibly control for time-varying firm, analyst, and local characteristics. These sets of high-dimensional fixed effects function collectively as a triple-difference design (Wooldridge, 2007). Our estimated effects come not only from comparing how the gap in green and non-green forecast accuracy varies over time for the same analyst, but also from further comparing this variation across analysts located in different MSAs. This design helps rule out a wide range of confounding factors at the firm, analyst, and MSA levels, as well as alternative explanations. For example, the analyst × firm fixed effect alleviates concerns that certain analysts—such as those based in Democratic-leaning MSAs—are systematically better at forecasting green firms for reasons unrelated to local EV adoption. Furthermore, local EV adoption is largely shaped by public infrastructure investments and automaker deployment strategies, rather than by analysts' own choices, making it plausibly exogenous to analysts' forecasting behavior.

To shed light on the mechanism underlying the improved forecast accuracy for green firms, we further provide three pieces of evidence that collectively support the attention and effort reallocation channel. First, we examine whether there is any net improvement in forecast accuracy across all firms during periods of heightened EV salience. 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, we find no such net improvement. Instead, while forecast accuracy for green firms improves, forecast errors for non-green firms increase 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.

Second, we investigate cross-sectional heterogeneity in the effect of EV adoption. We find that the improvement in forecast accuracy for green firms is more pronounced among analysts who are male, younger, less busy, and among green firms characterized by higher levels of information asymmetry. These patterns are consistent with an attention reallocation mechanism, whereby local EV salience selectively influences analysts who are the representative purchasers of EVs (Peters and Dütschke, 2014; Plötz et al., 2014), and are more flexible with cognitive resources. The stronger effect among green firms with greater information asymmetry 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.

Third, we directly examine how analysts allocate their forecasting efforts across firms. 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, 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 reinforce the notion that local green transition cues do not uniformly enhance analysts' forecasting capacity, but instead reallocate their attention and efforts toward sustainability-aligned firms.

Our findings have broader implications for understanding how local developments influence capital market outcomes through generalizable cues and salience. We show that local EV salience not only improves analysts' forecast accuracy for green firms through reallocating attention and efforts, but also generates market-level and firm-level consequences. Specifically, the stock market reacts more strongly to forecast revisions of green firms' EPS made by analysts experiencing high EV salience, suggesting that their enhanced attention leads to more informative forecasts for green firms. Moreover, this analyst-driven attention and effort contribute to a measurable improvement in the information environment of green firms, as measured by lower levels of bid-ask spread and Amihud (2002) illiquidity.

Taken together, our results suggest that the expansion of EV infrastructure—while primarily a transportation and environmental policy initiative—can have important spillover effects on financial markets. By shaping how analysts process and allocate attention, local EV development indirectly facilitates better capital market coverage for sustainability-aligned firms, potentially improving their access to financing and investor recognition.

Finally, we document that such strategic reallocation of effort also has important career implications for analysts themselves. Analysts with superior forecasting ability for green firms are more likely to become All-Star analysts in the following year. This evidence suggests that analysts' effort reallocation in response to emerging local trends is not only value-relevant for the market but also personally rewarding.

Our study contributes to the literature in several ways. First, we contribute to the literature that explores how the allocation and constraint 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 et al., 2019) and attention-distracting events (Driskill et al., 2020; Cuculiza et al., 2021; Bourveau et al., 2024; Han et al., 2024), as well as strategic allocation of resources due to career concerns (Harford et al., 2019). Further, analysts often pay attention to and make forecasts based on *firm-specific* local information, 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 providing novel evidence that *non-firm-specific* local cues (EV adoption) can actually enhance analysts' forecast accuracy for green firms by triggering a beneficial reallocation of limited attention and effort, illuminating how broader contextual cues can shape analysts' cognitive frameworks and direct their analytical resources toward certain companies.

Second, our study also contributes to the growing literature examining how analysts incorporate ESG information into their assessments. Prior research demonstrates that analysts integrate downside ESG risks into their outputs, adjusting both cash flow expectations and discount rates for financially material ESG incidents (Park et al., 2024). Negative ESG news prompts analysts to significantly downgrade their forecasts, particularly at longer horizons, with these revisions explaining most of the negative impact on firm value (Derrien et al., 2024). Other studies have examined how analysts address climate-related topics in earnings calls (Sautner et al., 2024) and in their written reports (Chan, 2024). However, existing literature primarily focuses on how analysts respond to explicit ESG information rather than how ambient environmental cues might shape their attention toward ESG-relevant firms. Our study contributes to this ESG literature by revealing how the physical manifestation of green transitions in analysts' local environments influences their assessment of environmentally friendly companies, highlighting an unexplored channel through which environmental awareness permeates financial analysis beyond formal ESG disclosures and explicit sustainability metrics.

Third, our paper contributes to the growing literature on the economic dimensions of electric vehicle adoption. Existing research explores various aspects of the EV transition—from retail demand spillovers at charging stations (Babar and Burtch, 2024; Zheng et al., 2024) to financing patterns revealing both higher interest rates for EVs (Bena et al., 2024) and lower default rates among EV owners (Klee et al., 2024). Studies on household behavior demonstrate that household characteristics and preferences significantly influence EV purchasing (Peters and Dütschke, 2014; Plötz et al., 2014; Bushnell et al., 2022). Building on this insight, we have reason to believe that similar personal characteristics influence how financial analysts—who are ultimately individuals with personal preferences—interpret and respond to EV trends in capital markets. Our study bridges this critical gap by examining how EV adoption patterns influence financial information intermediaries, extending our understanding beyond consumer markets into the broader financial ecosystem where personal characteristics may similarly affect professional judgments.

The remainder of the paper is structured as follows. Section 2 introduces the main testable hypotheses and discusses the theoretical mechanisms that underpin them. Section 3 describes the sample, data sources, and the construction of key variables. Section 4 presents the association between EV adoption salience and analyst forecast accuracy. Section 5 investigates the underlying mechanisms, with a particular focus on the reallocation of analysts' attention and efforts. Section 6 discusses the broader implications of our findings. Section 7 concludes.

2. Hypothesis Development

We examine whether salient local cues of the green transition trend, captured through the expansion of electric vehicle (EV) infrastructure, affect analysts' forecast accuracy for green firms. The expected effect of EV salience on forecast performance is theoretically ambiguous ex ante. It is possible that these contextual cues have no impact on the forecast performance of analysts, who have already utilized all available information in forecasting, which corresponds to our null hypothesis. If an effect does exist, however, it may be either positive or negative, and it may differ between green and brown firms, depending on how analysts respond to salient local cues.

While our motivation is rooted in whether salient cues shift analysts' attention allocation, such cues may also induce non-strategic responses that distort analysts' forecasts. Accordingly, we develop two testable hypotheses regarding the effect of local EV salience on analysts' forecasting. The first hypothesis is strategic attention reallocation, whereby analysts reallocate cognitive resources toward firms and topics perceived as more important. The second hypothesis is salience-driven overreaction, whereby heightened EV salience induces analysts to overweight salient information, leading to biased forecasts.

2.1. Attention Reallocation

EV salience may influence analysts' forecasting by altering how analysts allocate their limited attention and effort across covered firms. Prior research shows that analysts strategically reallocate attention toward firms that are more important for their career concerns (Harford et al., 2019). The expansion of EV infrastructure may serve as a salient local cue that highlights the ongoing green transition, drawing analysts' attention to firms that may become more economically important under this emerging trend. Consistent with this view, we posit that greater local EV salience induces analysts to strategically reallocate their attention across firms they cover.

H1: Greater local EV salience leads analysts to strategically reallocate attention toward firms that are perceived as more important.

Further, two distinct attention reallocation patterns may arise *ex ante*. First, EV salience may elevate the overall salience of sustainability as an analytical dimension, prompting analysts to devote more effort to understanding sustainability-related risks and opportunities across firms more broadly (Dhaliwal et al., 2012). Under this scenario, analysts may increase their effort devoted to both green and brown firms, as sustainability considerations become more central to firm valuation. Greater analytic effort, in turn, may improve forecast accuracy for both green and brown firms relative to other firms.

H1a: Greater local EV salience increases analysts' effort devoted to both green and brown firms, leading to improved forecast accuracy for these 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; Chen et al., 2025; Sautner et al., 2024). As a result, analysts may perceive firms that are well positioned to benefit from green transition opportunities as more important than other firms. In addition, analysts may be less inclined to devote marginal attention to brown firms when such attention would require emphasizing potential downside risks associated with environmental transition pressures (Lim, 2001).

H1b: Greater local EV salience increases analysts' effort devoted to green firms relative to non-green firms, leading to higher forecast accuracy for green firms.

2.2. Salience-Driven Overreaction

Beyond strategic attention reallocation, EV salience may also influence analysts' forecasting through a behavioral channel driven by salience-induced distortions. According to salience theory (Bordalo et al., 2012), individuals tend to overweight vivid, salient, and symbolically powerful information when forming beliefs, even when such information is only partially informative about fundamentals.

The diffusion of electric vehicles represents a highly visible and symbolically salient manifestation of the green transition. As a result, heightened local EV salience may cause analysts to disproportionately emphasize ESG considerations when forecasting firm performance. When analysts overweight salient ESG-related signals relative to other value-relevant information, their forecasts may deviate from fundamentals, leading to reduced forecast accuracy. For firms perceived as benefiting from the green transition, analysts may become overly optimistic, resulting in inflated earnings forecasts. In contrast, for firms perceived as being adversely affected by environmental transition pressures, analysts may become excessively pessimistic, leading to overly conservative forecasts.

H2: Greater local EV salience induces analysts to overreact to salient green transition cues, leading to lower forecast accuracy overall, overly optimistic forecasts for green firms, and overly pessimistic forecasts for brown firms.

3. Sample Description, Variable Construction, and Summary Statistics

3.1. Electric Vehicle Adoption

We proxy local electric vehicle (EV) adoption using data on EV chargers, as charging infrastructure is essential for EV development (Springel, 2021; Rapson and Muehlegger, 2023). EV charger data is obtained from the Alternative Fuels Data Center (AFDC) provided by the US Department of Energy, which offers detailed city-level records, including the total number of chargers, charger types, operational statuses, etc. We further aggregated the city-level data to the Metropolitan Statistical Area (MSA) level, as the MSA level is more likely to cover analysts' working and residential areas.

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 measures are defined as below,

$$EV\ Salience_{k,q} = \frac{\Delta EV\ Chargers_{k,q}}{Land\ Area_k}, \tag{1}$$

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

To illustrate the spatial and temporal variation in EV adoption, we present two complementary figures. Figure 1 displays the geographic distribution of EV charger density across US metropolitan areas in the contiguous 48 states in 2015Q1 and 2020Q1. These snapshots capture a period of rapid EV infrastructure expansion and reveal substantial cross-sectional heterogeneity in charger density across MSAs. Figure 2 builds on this by illustrating quarterly EV charger growth in the five MSAs with the fastest cumulative expansion between 2010 and 2020. In addition to differences in the overall magnitude of adoption, the figure shows heterogeneity in adoption trajectories across locations. For instance, New York experiences a moderate but noticeable increase around 2016–2017, while San Jose undergoes a sharp surge in charger deployment closer to 2019–2020, during which New York's growth becomes relatively stable. This variation in EV adoption patterns over time across different MSAs provides a rich empirical setting for examining how local environmental salience shapes analyst behavior. Furthermore, notable growth in EV adoption emerges starting from 2015;[3] thus, we select 2015 as the starting year for our sample period. To mitigate potential

[2] As robustness checks, we use population-scaled EV salience, log value of new EV chargers, and land-area-scaled total count of EV chargers as independent variables. The data of land area and population are sourced from the US Census Bureau.

[3] This growth was driven by multiple factors: (1) strengthened clean transportation policies following the 2015 Paris Climate Agreement; (2) significant decline in lithium-ion battery costs around 2015, reducing EV manufacturing costs; (3) continued impact of federal tax incentives (up to $7,500) in the US; (4) shifting

confounding effects arising from COVID-19, we conclude the analysis in the first quarter of 2020.

To better understand the factors driving EV adoption and assess the plausibility of our identification strategy, 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. Consistent with prior surveys and studies on EV adoption (Union of Concerned Scientists and Consumer Reports, 2022; Davis et al., 2025), we find that areas with higher share of Asian population and stronger Democratic political leanings exhibit significantly greater EV infrastructure expansion in the full MSA sample. Beyond demographics and political preferences, we also find that energy prices (particularly gas prices), climate concern levels, EV-related policy environments, and commute times are significant predictors of local EV salience.[4]

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%, suggesting substantial unexplained variation remains. Much of the residual variation in EV charger deployment likely stems from supply-side factors largely exogenous to analysts' forecasting behavior, including the timing of technical approval processes (land use permits, environmental assessments, grid connection authorizations), charger manufacturers' production capacity and installation schedules, and required electrical infrastructure upgrades. These supply-side factors are unobservable to individual analysts, and their quarter-to-quarter timing is effec-

consumer perceptions after Tesla Model S gained popularity since its 2012 launch; and (5) introduction of more affordable EV models during 2015-2017 (e.g., Chevrolet Bolt).

[4]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.

tively unpredictable and uninfluenceable from any single analyst's perspective. This lends credibility to our identifying assumption that the precise timing of local EV infrastructure expansion represents a plausibly exogenous variation in local green salience that shapes analysts' attention allocation.

Furthermore, we note that analysts in our sample are disproportionately concentrated in large metropolitan areas with predominantly Democratic-leaning populations. This concentration helps explain why the Democratic vote share variable loses statistical significance in the analyst sample (Panel A) compared to the full MSA sample (Panel B), thereby mitigating concerns that partisan political preferences might confound our main findings.

3.2. Analyst

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 specifically on one-quarter-ahead EPS forecasts, as our objective is to examine analysts' timely forecasting activities.

We link the I/B/E/S forecast data to stock prices obtained from the Center for Research in Security Prices (CRSP) database to compute forecast accuracy, our main dependent variable, which is inversely proxied by the forecast error. Specifically, the forecast error for analyst i's (in MSA k) forecast issued at time t for firm j's earnings in fiscal quarter q is defined as:

$$Forecast\ Error_{i,j,k,q,t} = \left| \frac{E\hat{P}S_{i,j,k,q,t} - EPS_{j,q,t}}{P_{j,t-1}} \right|, \tag{2}$$

where $E\hat{P}S_{i,j,k,q,t}$ is analyst i's (in MSA k) most recent forecast of EPS issued in quarter q of year t for firm j, $EPS_{j,q,t}$ is the actual EPS for firm j in quarter q of year t, and $P_{j,t-1}$ denotes firm j's stock price at the end of the prior calendar year $t-1$. 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 further merge the I/B/E/S forecast 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.

3.3. 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 impact—and considering that analysts typically specialize in specific industries—we define green firms within industry. 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. Within each FF12 industry, we classify green firms as those in the bottom 20% in terms of Scope 1 emission intensity (scaled by revenue). For robustness, we also construct alternative definitions using the bottom 33% emission thresholds.

3.4. 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 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 mean EV salience is 0.0055, indicating that, on average, an MSA adds approximately 5 new EV chargers per 1,000 square miles each quarter.[5] This corresponds 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.

[5]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 vehicles along with environmental preferences and policy.

4. EV Salience and Forecast Accuracy

4.1. Baseline Result

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

$$Forecast\ Error_{i,j,k,q} = \beta_1 EV\ Salience_{k,q} \times Green\ Firm_{j,q} + \mathbf{X}_{i,j,q} + \mathbf{FEs} + \varepsilon_{i,j,k,q}, \quad (3)$$

where $Forecast\ Error_{i,j,k,q}$ indicates the forecast error of analyst i residing in MSA k for firm j in quarter q, $EV\ Salience_{k,q}$ indicates the EV salience of MSA k in quarter q, $Green\ Firm_{j,q}$ is a dummy variable that 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. We control for granular fixed effects across the specifications. Therefore, $\mathbf{X}_{i,j,q}$ that denotes control variables only include *Forecast Age*, which is the natural logarithm of the number of calendar days from the forecast to the earnings announcement date (Clement, 1999) (Table 1 reports raw number of days for ease of interpretation). The standard errors are clustered at the MSA level. If EV salience catches analysts' attention and triggers analysts to put more effort into green firms, we should observe a negative β_1, indicating that the growth of EV salience is associated with a reduction in analysts' forecast errors of green firms. Alternatively, if analysts overreact due to the salience of a local expansion of EV chargers and underweight the signal from the financial factors of green firms, we expect a positive β_1.

Table 2 presents the regression results. Our variable of interest, $EV\ Salience \times Green\ Firm$, is negatively related to forecast error across all four specifications under different combinations of fixed effects. This indicates that local cues of EV adoption enhance forecast accuracy on green firms relative to other firms, providing evidence consistent with the attention reallocation hypothesis (H1) and inconsistent with the salience-driven overreaction hypothesis (H2). Throughout the specifications, we include firm × quarter and MSA × quarter (or analyst × quarter fixed effects that subsume MSA × quarter) fixed effects that absorb time-invariant and time-varying characteristics at the firm and MSA level. Thus, we eliminate concerns about firm-/MSA-specific impacts such as firm-specific ESG initiatives or local economic and regulatory environments. In Column 3, we further control for analyst × quarter fixed effects, ruling out the possibility that analysts with different levels of skill exhibit different interest and accuracy in green firms. In our most stringent specification as outlined in Column 4, we control for analyst × firm fixed effects, ensuring that our results are not driven by certain analysts systematically covering particular green firms with different levels of accuracy over time, and ruling out the possibility that analysts provide more accurate forecasts for local firms (Malloy, 2005; Bae et al., 2008). Even with these extensive fixed effects, the coefficient on $EV\ Salience \times Green\ Firm$ remains significantly negative at the 1% level, suggesting a robust relationship between local EV salience and improved forecast accuracy for green firms.

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,[6] and 5.67% more accurate forecasts when scaled by green firms'

[6]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-

mean forecast error.[7] Regarding our most stringent specification, the associated economic significance is 3.02% and 5.20%.[8] Compared with *Forecast Age* in Column 3, the effect of an interquartile increase in local EV salience is equivalent to having analysts forecast 54 days closer to earnings announcements at the median forecast age of 78 days.[9]

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* × *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 provides evidence inconsistent with the hypothesis that EV salience induces analysts to develop broad ESG-related knowledge (H1a). If EV salience prompted general ESG integration, we would expect improved forecast accuracy for both green and brown firms. Instead, the lack of improvement for brown firms suggests analysts do not uniformly

0.0015)×0.0843/0.0179)×100%=3.30%.

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

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

[9] 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.

enhance ESG analysis across their coverage. This asymmetry aligns with our hypothesis that analysts tend to selectively allocate attention toward firms presenting growth opportunities rather than regulatory or transition risks (H1b) (Chan, 2024). Consistent with this interpretation, our subsequent analyses focus primarily on green firms, as they represent the category where local EV salience most meaningfully shapes analyst behavior and information production.

For these economically significant results to have a causal interpretation, our key independent variable (EV salience) should be exogenous to analyst forecast accuracy. First, our stringent specification controls for a comprehensive set of fixed effects, eliminating any time-invariant or time-variant confounding variables at the firm, MSA, and analyst levels, such as changes in firms' disclosure environments, regional shocks, and analysts' forecasting skills. Second, different MSAs exhibit substantial heterogeneity in EV salience changes alongside temporal fluctuations. This pattern mitigates selection bias concerns (e.g., analysts residing in environmentally progressive regions having persistently high climate concerns and superior forecast accuracy) as our identification leverages within- analyst temporal variations in EV salience as well. Notably, as shown in Figure 2, MSAs with the most EV salience growth are mostly predominantly Democratic-leaning MSAs with presumably similar levels of climate concerns, while we still observe significant relative improvements in forecast accuracy. This suggests that our results are driven by temporal variations in local EV adoption cues rather than by systematic differences in analyst characteristics across regions. Third, reverse causality is unlikely to be an issue since changes in analyst forecast accuracy would not reasonably influence trends in EV salience, which are predominantly driven by EV manufacturer expansion and public infrastructure development by local governments.

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 quarters t through $t+5$, where t represents the baseline quarter. The results reveal that the positive effect of EV salience on green firm forecast accuracy is strongest in the contemporaneous quarter (t), with the effect gradually dissipating over time. By quarter $t+4$, the effect becomes statistically indistinguishable from zero. This pattern suggests that while local EV salience captures analysts' attention and improves their near-term forecasting performance for green firms, the salience of these environmental cues naturally fades over time.

4.2. Robustness

4.2.1. Alternative Measures and Samples

To ensure the validity of our results, we run a battery of robustness checks to examine whether the results still hold under alternative samples and measures of EV salience. First, consistent with prior studies, analysts from New York make up 56.9% of the entire analyst universe of the sample (Cuculiza et al., 2021; Gerken and Painter, 2023). Therefore, we exclude analysts from New York to eliminate the concern of local factors in New York driving our results. Column 1 of Table A.3 reports the regression result. The coefficient drops marginally from -0.0843 to -0.0726, but remains statistically significant at the 1% level, suggesting samples excluding New York still exhibit effective variation in local EV salience.[10]

Second, to further mitigate selection bias, we restrict the sample to analysts who entered

[10]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.

the workforce before 2003, the year Tesla was founded. This ensures their initial location choices were made when EV market awareness was minimal, separating pre-existing environmental preferences from subsequent exposure to local EV infrastructure growth. Focusing on this cohort, we isolate the impact of changing EV infrastructure development (which occurs after their location choices were made) from any selection effects driven by pre-existing environmental consciousness. 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 of Table A.3 remain significantly negative at the 1% level. Moreover, it is unlikely that analysts dynamically relocate in response to evolving local environmental conditions. Analyst mobility is generally low, and most analysts do not change their residential MSA over time (Park et al., 2024), making it implausible that environmentally oriented analysts systematically move to greener regions as local EV adoption increases.

Third, to address the concern that our results may be indirectly driven by changes on the firm side—that is, local EV salience affecting firms' own behavior or performance and subsequently influencing analysts' forecast effort—we restrict the sample to cases where analysts and firms are located in different MSAs. This design ensures that the analysts' exposure to local EV salience is decoupled from the green transition dynamics of the firms they cover. Column 3 of Table A.3 shows that our results remain robust even after excluding same-MSA analyst-firm pairs, with the coefficient on $EV\ Salience \times Green\ Firm$ remaining negative and statistically significant at the 1% level.

Fourth, to ensure our results are not mechanically driven by analysts covering firms with direct business exposure to the EV industry, we exclude firms in automobile-related industries (e.g., Motor and Generator Manufacturing, Tire and Tube Merchant Wholesalers, Passenger Car Leasing, etc.) as classified by their 6-digit NAICS codes. Column 4 of Table A.3 shows that our findings persist after excluding these firms, with the coefficient on *EV Salience* × *Green Firm* remaining negative and statistically significant at the 1% level.

Finally, we use alternative EV salience measures and thresholds to determine green firms and check whether our result is sensitive to the construction of independent variables. In Columns 4-6 of Table A.3, we change the denominator of EV salience to the local population, use the log value, or the cumulative count of newly established EV chargers. In Column 7, we require green firms to be those with Trucost Scope 1 emission intensity below the 33% quantile or median within its FF12 industry for the relevant fiscal year. We still obtain a negative coefficient with significance at the level of 1% or 5% throughout the specifications.

4.2.2. More Stringent Controls and Fixed Effects

To further rule out potential confounding factors, Table A.4 presents results under more stringent specifications. Columns 2 and 4 include MSA × year × green firm fixed effects, which absorb all time-varying MSA-level factors that might differentially affect forecast accuracy for green versus non-green firms. This triple-interaction fixed effect ensures that our identification comes from within-MSA-year-green firm group variation in analyst EV salience exposure, ruling out the possibility that certain MSAs systematically produce better forecasts for green firms during specific periods due to local economic conditions, policy environments, or other regional factors.[11] Additionally, Columns 3 and 4 control for inter-

[11] The only alternative channel not fully absorbed by our most stringent fixed effects is the local institutional investors' demand for information of green firms at the MSA × year-quarter × green firm level. In untabulated tests, we find that our results are stronger among firms with lower institutional investors' average EV exposure, suggesting that local institutional demand is unlikely to drive our findings.

actions between green firm status and key MSA characteristics that significantly predict EV adoption in Table A.2 (demographic composition, energy prices, policy environment, and household characteristics). These controls ensure our results are not driven by these MSA-level factors directly affecting green firm forecast accuracy. The coefficient on EV Salience × Green Firm remains negative and statistically significant across all specifications, confirming the robustness of our baseline findings.

4.2.3. Forecast Optimism

In addition to examining analyst forecast accuracy, we also analyze how EV salience affects analysts' forecast optimism on green firms. The results are reported in Table A.5. We define *Forecast Optimism* as the difference between the analyst's forecasted EPS and the actual reported EPS, scaled by the share price on the last trading day of the previous calendar year. A higher value indicates more optimistic earnings forecasts. The results show that the coefficient on *EV Salience* × *Green Firm* is small and statistically insignificant across specifications, indicating that analysts in areas with high EV salience do not systematically develop more optimistic projections for green firms. This finding further provides evidence against the salience-driven overreaction hypothesis (H2).

5. How Analysts Achieve Better Forecast for Green Firms

In this section, we explore the mechanisms under which analysts make more accurate forecasts for green firms.

5.1. Net Improvement or Limited Attention Reallocation?

Our analysis has established that local EV salience enhances analysts' forecast accuracy for green firms relative to non-green firms. However, an important question remains: Does this improved accuracy represent a net improvement in overall forecasting performance, or does it fundamentally reflect a reallocation of analysts' limited attention? Intuitively, EV salience should not lead to an overall improvement in forecast accuracy, as EV infrastructure does not provide fundamental information about companies or industries but serves only as a salient local cue rather than genuine value-relevant information. Nevertheless, testing for the presence (or absence) of a net improvement remains critical. Our study is built on the assumption of limited attention, and demonstrating that the observed effects reflect a reallocation of limited cognitive resources—rather than a net gain in forecasting ability—is essential for establishing the theoretical foundation of our research.

We investigate whether EV salience leads to an overall improvement in forecast accuracy or if benefits for green firms come at the expense of non-green firms. Table 3 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 model specifications with different fixed effects,[12] 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% significance level, indicating that

[12]Unlike baseline regressions, we only include firm × fiscal-quarter fixed effects and either MSA or analyst fixed effects. Including MSA × quarter or analyst × quarter fixed effects would absorb the independent variable *EV Salience*.

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 attention rather than achieving net improvements in forecasting ability. The presence of local EV salience appears to redirect analysts' cognitive resources toward green firms at the expense of non-green firms, resulting in insignificant change in overall forecasting performance.

5.2. Cross-Sectional Regressions

We attribute the effect of EV salience on forecast accuracy to local cues drawing analysts' attention toward green firms. In this section, we conduct a series of cross-sectional tests at both the analyst and firm levels to further validate our findings.

5.2.1. Analyst-Level Heterogeneity: Analyst Attention

Analysts may exhibit heterogeneous responses to local EV salience. For instance, the presence of EV charging infrastructure may primarily capture the attention of specific demographic groups, while others remain unaffected by such contextual cues. Both industry reports and academic research indicate that young to middle-aged males demonstrate a stronger propensity to purchase EVs (Peters and Dütschke, 2014; Plötz et al., 2014; Cox Automotive, 2023). Consequently, we hypothesize that younger and male analysts in our sample would be more responsive to local EV salience, resulting in enhanced forecast accuracy for green firms. In Columns 1-2 of Table 4, we split the sample by analyst gender. Consistent with our expectations, male analysts exhibit significantly improved forecast accuracy for green firms when exposed to heightened EV salience. The regression coefficient of $EV\ Salience \times Green\ Firm$ for the male analyst subsample increases in magnitude to -0.0944 compared to our baseline model. An F-test confirms that the differential effect of EV salience between male and female analysts is statistically significant ($p < 0.01$). Furthermore, in Columns 3-4, we divide the sample based on analysts' median age as of 2015 to investigate whether younger analysts demonstrate greater sensitivity to local EV salience. As expected, the coefficient of $EV\ Salience \times Green\ Firm$ is larger in magnitude for younger analysts at the 5% significance level, although the difference in coefficients between age groups is statistically insignificant.

We further investigate how analysts' limited attention affects their response to local EV salience. Research has shown that financial analysts suffer from cognitive constraints that limit their ability to process available information (Hirshleifer et al., 2019; Bourveau et al., 2024). These attention constraints become particularly binding when analysts must divide their cognitive resources across many firms in their coverage portfolios. Consequently, "busy" analysts with larger portfolios may lack mental bandwidth to notice local EV salience and reallocate efforts. In contrast, analysts with smaller workloads may be more attuned to these local cues, triggering them to put effort into analyzing green firms and achieve better forecast accuracy. Following Harford et al. (2019), we classify analysts as "busy" if their portfolio size in a given year exceeds the median. We hypothesize that "non-busy" analysts would exhibit superior forecast accuracy for green firms in response to increased EV salience, given their enhanced capacity to recognize and process these local cues. Columns 5-6 of Table 4 reveal a substantial difference in how busy and non-busy analysts respond to local EV salience. The coefficient for $EV\ Salience \times Green\ Firm$ is -0.0456 for busy analysts compared to a considerably larger -0.1592 for non-busy analysts, with this difference being statistically significant (F-test p=0.006). These findings support our hypothesis that analysts with smaller portfolios possess greater cognitive capacity to identify and incorporate local cues into their forecasts for green firms, while busy analysts' attentional constraints impede their ability to effectively process these cues.[13]

Taken together, these cross-sectional tests support our attention-based hypothesis, showing that local EV salience improves green firm forecast accuracy primarily among young and male analysts, and analysts who are less busy. These findings confirm that both demographic factors and cognitive bandwidth significantly influence how analysts translate local EV salience into improved forecasting performance.

5.2.2. Firm-Level Heterogeneity: Information Asymmetry

After examining analyst-level heterogeneity, we now investigate how firm characteristics, particularly information asymmetry, moderate the relationship between EV salience and forecast accuracy. 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. For information-transparent firms, the marginal benefit of additional analyst attention may be limited, as these firms already enjoy thorough scrutiny from market participants. Conversely, high information asymmetry firms typically receive less attention and have fewer information intermediaries, creating greater opportunities for attentive analysts to discover and incorporate value-relevant information. When local EV salience stimulates analysts to direct more cognitive resources toward green firms, this enhanced attention should yield greater improvements in forecast accuracy for firms characterized by significant information

[13]This finding echoes Chan (2024), who shows that integrating climate change issues is costly and typically occurs when they face fewer time constraints or reduced competitive pressures in their coverage areas.

gaps.

To test this hypothesis, we examine how the effect of EV salience on green firm forecast accuracy varies across different dimensions of information asymmetry. Table 5 presents subsample regression results using classifications that capture both traditional information asymmetry and ESG-related transparency. Specifically, we classify firms with following characteristics as firms with high information asymmetry: low market cap (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), and no stakeholder engagement policy (not disclosed in 10-K or CSR reports that year).[14]

The results demonstrate a consistent pattern across all specifications. The effect of EV salience on green firm forecast accuracy is concentrated among firms with high information asymmetry. For traditional information asymmetry measures, the effects are particularly pronounced in the high-asymmetry subsamples: the coefficient on $EV\ Salience \times Green\ Firm$ is -0.2832 (p<0.01) for small-cap firms in Column 1, compared to -0.0017 (insignificant) for large-cap firms in Column 2. Similarly, firms with low analyst coverage exhibit a coefficient of -0.2512 (p<0.10) in Column 3, while those with high coverage show -0.0378 (p<0.05) in Column 4, indicating a substantially weaker effect. The F-tests confirm these differences are statistically significant (p=0.000 and p=0.001, respectively). The ESG-related transparency measures in Columns 5-8 reveal similar patterns. The coefficient on $EV\ Salience \times Green\ Firm$ is -0.1519 (p<0.01) for firms without CSR reports in Column 5,

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

versus 0.0049 (insignificant) for firms with CSR reports in Column 6 (F-test p=0.000). Likewise, firms lacking stakeholder engagement policies exhibit a coefficient of -0.0977 (p<0.01) in Column 7, compared to 0.0025 (insignificant) for those with such policies in Column 8 (F-test p=0.030).

These findings collectively support our hypothesis that the attention-enhancing effects of local EV salience are particularly valuable for green firms characterized by high information asymmetry–whether measured through conventional indicators or ESG-related disclosure gaps. Analysts have limited cognitive resources to gather and process information, so when their attention is reallocated toward these previously under-scrutinized firms due to heightened EV salience, they make more accurate earnings forecasts. Our results are consistent with prior literature documenting the importance of analyst attention in reducing information asymmetry (Harford et al., 2019; Hirshleifer et al., 2019; Bourveau et al., 2024), while highlighting the novel role of local salient shocks signaling economic transition in directing this attention.[15]

5.3. Analyst Effort Reallocation

Building on the evidence that EV salience enhances forecast accuracy through heightened analyst attention, we next examine whether this increased attention translates into tangible analyst effort directed toward green firms. This section investigates how local cues of EV salience affect the effort that analysts exert in analyzing green firms.

[15] Driskill et al. (2020) suggest that analysts tend to allocate limited attention to firms with rich information environments in the presence of concurrent announcements. Our results do not contradict theirs because our claim is that analysts' attention is reallocated to green firms, but green firms with a worse information environment gain relative forecast accuracy. In other words, analysts do not reallocate attention deliberately to firms with bad information environments, but ultimately (green) firms with bad information environments become better off in terms of forecast accuracy.

We measure analyst effort along three complementary dimensions. First, we examine the frequency of earnings forecast revisions for green firms as a proxy for effort allocation. Second, we assess analysts' qualitative engagement during earnings conference calls, focusing on their climate-related interactions with management. Third, we analyze analyst reports to evaluate whether EV salience increases the likelihood of incorporating environmental themes—particularly those related to climate opportunities such as electric vehicles and renewable energy. Together, these measures provide a multifaceted view of how analysts reallocate limited attention and effort in response to locally salient environmental cues.

5.3.1. Earnings Forecast Update 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., Loh and Stulz, 2018; Harford et al., 2019). It captures analysts' proactive behavior in response to evolving information and reflects the resources allocated to firm-specific analysis.

The forecast frequency is proxied by 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 scaling with the mean number of forecasts issued by all analysts for firm j in quarter q (Bourveau et al., 2024).

As shown in Table 6, the coefficient on $EV\ Salience \times Green\ Firm$ is significantly positive for both *Relative Frequency* and *Scaled Frequency*. These results indicate that higher EV salience in an analyst's local area is associated with increased forecast update frequency for green firms relative to non-green firms, thus demonstrating that EV salience enhances tangible analyst effort directed toward green firms. 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 terms of relative frequency, and 7.31% in terms of scaled frequency.[16] These results remain robust after controlling for the firm × fiscal-quarter and the analyst × year-quarter fixed effects.

5.3.2. Analyst Engagement in Earnings Calls

To capture analysts' forecasting effort beyond revision frequency, we examine their engagement in earnings calls. We obtain the data on analysts' climate-related questions during earnings calls from Sautner et al. (2024). This setting provides a meaningful behavioral signal, as earnings calls are a key venue where analysts interact directly with firm management and the questions analysts ask reflect the most important issues they pay attention to.

Table 7 presents the results. The key independent variable is the interaction between *EV Salience* and *Green Ratio*, defined as the proportion of green firms in an analyst's coverage portfolio in the current year. The dependent variable in Column 1 is an indicator equal to one if the analyst asked at least one climate-related question during an earnings call in a given quarter. We find that analysts with higher green exposure in their coverage portfolio are significantly more likely to raise climate-related questions when local EV salience is high.

[16] 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) × 1.0542/0.1075) × 100% = 6.86% for the relative frequency and ((0.0085-0.0015) × 0.7095/0.0679) × 100% = 7.31% for the scaled frequency.

These results remain robust after controlling for the analyst × year fixed effect and the MSA × year-quarter fixed effect. This result sheds further light on our proposed mechanism: analysts not only shift attention and effort toward green firms, but also engage more actively with the climate-related issues of these firms.

Columns 2 and 3 further decompose the nature of climate-related questions into distinct categories. Column 2 examines climate questions that capture conventional firm value implications (e.g., earnings, cost, margins), while Column 3 focuses on climate-related questions referencing broader ESG-related value concepts (e.g., sustainability goals, green strategy). Interestingly, while both coefficients are positive and similar in magnitude, only the estimate for values-related questions in Column 3 achieves statistical significance. These results likely reflect the fact that, given our definition of green firms, questions related to green strategy and sustainability goals are more relevant, whereas climate-related valuation concerns (as captured in ClimateValue) are likely more relevant for brown firms, which face direct financial risks from regulation, stranded assets, or transition costs.

5.3.3. Analyst Reports

To further capture analysts' effort allocation, we examine the textual content of analyst reports. Specifically, we assess whether analysts in high-EV-salience MSAs are more likely to adopt climate-related language in their reports, particularly when they cover more green firms. We construct analyst-level measures of climate-related report content using textual data from the Mergent Investext database. For each analyst, we search their published reports for the presence of specific keyword groups during our sample period, and create indicator variables that capture whether those keywords appear.

We consider two categories of environmental terms. First, we include EV-specific bigrams including "electric vehicle(s)" and "charging station(s)" to directly capture the analyst's engagement with topics related to EV adoption. Second, we adapt and expand upon the climate-related bigram framework from Sautner et al. (2023), which derives bigrams from firm earnings call transcripts, to examine analysts' environmental language in written reports. Specifically, we extract both (i) the top five climate-related bigrams overall and (ii) the top five bigrams 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")—to capture different dimensions of ESG emphasis.[17]

Table 8 presents how EV salience shapes analysts' report content, conditional on their exposure to green firms. Column (1) shows that during EV-salient period, analysts covering a higher share of green firms are significantly more likely to mention EV-specific terms—such as "electric vehicle(s)" and "charging station(s)"—in their reports during high-EV periods. Column (2) extends this finding to a broader set of climate-related bigrams, revealing a significant increase in the use of climate-related language. Crucially, this effect remains significant even after removing EV-specific phrases from the bigram set, as shown in Column (3), suggesting that analysts are not merely echoing the local salience cue, but are engaging with broader environmental themes. Columns (4) to (6) decompose the climate bigrams into three subcategories: opportunity-related, regulation-related, and physical risk-related phrases. Notably, the increased climate attention is concentrated in opportunity-oriented

[17]Due to technical constraints of the Mergent Investext database, we are unable to download and process the full text of all analyst reports for textual analysis. Instead, we identify whether each analyst issued at least one report during the sample period that contains any phrase from a given group of keywords. In practice, the search process becomes prohibitively slow when the number of keywords in the group exceeds five, which motivates our use of the top five bigrams within each category.

language (Column 4), while we find little to no increase in the use of bigrams related to climate regulations or physical climate risks. This selective emphasis on opportunity-oriented language highlights that local EV salience sharpens analysts' attention toward forward-looking, values-relevant climate opportunities, rather than the downside aspects of climate risk narratives or regulations.

This pattern is consistent with the interpretation that EV salience reallocates analyst attention toward green firms, and that this reallocation is reflected in a greater emphasis on climate-related opportunities. Since green firms are more likely to benefit from the green transition—due to their business models being thematically aligned with environmental innovation and sustainability—analysts covering these firms may naturally frame their reports around forward-looking opportunity narratives. In contrast, brown firms, whose climate exposure is more often framed in terms of regulatory burden, are less likely to be the focus of opportunity-oriented analyst output. Thus, the observed increase in opportunity-related language reflects not only a shift in climate attention, but also a selective deepening of engagement with green firms in response to salient local environmental cues.

6. Market Reaction, Economic Consequences, and Analyst Career Outcomes

In this section, we further investigate the economic consequences of EV salience through analyst forecasting. Specifically, we test whether investors recognizes the value of the forecast revisions made by analysts experiencing high EV salience and the effect of such analysts' forecasts on green firms' information environment.

6.1. The Market Reaction to Forecast Revisions

Since EV salience triggers analysts to put more effort into analyzing green firms, they may obtain valuable and unique information. Given that both the effort and the increased accuracy are observable, we expect stock prices to respond more strongly to forecast revisions of green firms' EPS made by analysts experiencing a higher level of EV salience. To test the prediction, we estimate the following regression model:

$$\begin{aligned} CAR_{i,j,k,q,t} = {} & \beta_1 EV\ Salience_{k,q} \times Green\ Firm_{j,q} \times Forecast\ Revision_{i,j,k,q,t} \\ & + \beta_2 EV\ Salience_{k,q} \times Green\ Firm_{j,q} + \beta_3 EV\ Salience_{k,q} \times Forecast\ Revision_{i,j,k,q,t} \\ & + \beta_4 Green\ Firm_{j,q} \times Forecast\ Revision_{i,j,k,q,t} + \beta_5 Forecast\ Revision_{i,j,k,q,t} \\ & + \mathbf{X}_{i,j,q} + \mathbf{FEs} + \varepsilon_{i,j,k,q,t}, \end{aligned} \tag{4}$$

where $CAR_{i,j,k,q,t}$ indicates cumulative abnormal returns for firm j during the window of [0, 3] days of forecast revision of analyst i' residing in MSA k at time t in quarter q, adjusted by either CAPM or Fama-French 3 factor model; $Forecast\ Revision_{i,j,k,q,t}$ is the difference between analyst i's current earnings forecast for firm j at time t 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. The other variables are identically defined as Equation (3).

Table 9 reports the regression results. Consistent with prior studies (Gleason and Lee., 2003; Green et al., 2014; Hirshleifer et al., 2019), the coefficient for *Forecast Revision* is positive and statistically significant, suggesting analyst forecast revisions contain information and the market responds to them. Furthermore, the coefficient for *EV Salience* $\times$ *Green Firm* $\times$ *Forecast Revision* is positive and statistically significant at the 5% level for both specifications. The magnitude of the coefficient is similar in both specifications. The results suggest that the stock market reacts more strongly to forecast revisions issued by analysts experiencing a high level of EV salience, as such revisions contain valuable information through analysts' attention and effort that they put into.

6.2. Effects on Firms' Information Environment

Next, we explore whether the coverage by analysts experiencing high EV salience leads to real consequences for the information environment of firms. In Section 5.2.2, we find that EV salience primarily affects analysts' forecast of green firms with a poor information environment. Therefore, the forecasts provided by analysts who dedicate additional attention and effort tend to improve firms' information environment. We estimate the following regression to conduct the test,

$$\begin{aligned} Information\ Asymmetry_{j,q} = & \ \beta_1 EV\ Salience\ Exposure_{j,q} \times Green\ Firm_{j,q} \\ & + \beta_2 EV\ Salience\ Exposure_{j,q} \\ & + \mathbf{X}_{j,q} + \mathbf{FEs} + \varepsilon_{j,q}, \end{aligned} \tag{5}$$

where $Information\ Asymmetry_{j,q}$ is proxied by either bid-ask spread or Amihud (2002) illiquidity measure for firm j in quarter q; $EV\ Salience\ Exposure_{j,q}$ is firm j'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 q in all the MSAs of analysts covering the firm in the year, scaled by the sum of land area of the corresponding MSAs. A lower level of bid-ask spread or Amihud's illiquidity indicates a better information environment, thus we expect a higher EV salience exposure will reduce the level of the two information asymmetry measures for green firms, i.e., a negative β_1.[18] In the spirit of Harford et al. (2019) and 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, etc. We also include firm fixed effects and year-quarter fixed effects, and cluster the standard errors at the firm level.

The results are presented in Table 10. We find a negative and statistically significant coefficient on the interaction term $EV\ Salience\ Exposure \times Green\ Firm$ across both measures of information asymmetry, indicating the attention and effort devoted by analysts in high EV salience regions translate into real economic benefits for green firms by improving their information environment. In contrast, the coefficient on *EV Salience Exposure* alone is not statistically significant, confirming that these information environment benefits are specific to green firms rather than applying to all firms covered by analysts from high EV salience areas.

6.3. Analyst Career Outcomes

Lastly, we examine the effect of analysts' forecasting performance of green firms on their career outcomes. We estimate a logit regression to investigate how analysts' forecasting performance on green firms affects the probability of being recognized as an All-Star analyst. Our dependent variable is an indicator equal to one if the analyst becomes an All-Star analyst in the next year, which is obtained from the October issues of *Institutional Investor*

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

magazine. Our key independent variables capture analysts' forecasting performance for green firms. Specifically, we have two models as follows:

$$\begin{aligned} \Pr(\text{All-Star Analyst}_{i,t+1}) = \beta_0 &+ \beta_1 \text{Forecast Error (Green Firms)}_{i,t} \\ &+ \beta_2 \text{Forecast Error (Non-Green Firms)}_{i,t} \\ &+ \mathbf{X}_{i,t} + \text{Year FE} + \varepsilon_{i,t}, \end{aligned} \tag{6}$$

$$\begin{aligned} \Pr(\text{All-Star}_{i,t+1}) = \beta_0 &+ \beta_1 \text{Green Outperformance}_{i,t} \\ &+ \mathbf{X}_{i,t} + \text{Year FE} + \varepsilon_{i,t}, \end{aligned} \tag{7}$$

In Equation (6), we include analyst i's average forecast errors for green firms and non-green firms in year t simultaneously to conduct a horse-race test. In Equation (7), we construct a dummy variable, $Green\ Outperformance_{i,t}$, which equals one if analyst i's average forecast error for green firms in year t is smaller than that for non-green firms, and zero otherwise. This indicator captures analysts' relative forecasting advantage in green firms compared to non-green firms. In both specifications, $\mathbf{X}_{i,t}$ denotes a vector of control variables, including the analyst's All-Star status in the current year, the number of firms covered, analyst gender, age, and the proportion of green firms in the analyst's coverage portfolio.

Table 11 reports the estimation results. Column (1) shows that analysts with lower forecast errors for green firms are significantly more likely to be selected as All-Stars in the subsequent year. In Column (2), we replace the separate forecast error measures with *Green Outperformance*, which captures the relative forecasting advantage on green firms compared to non-green firms. The coefficient on *Green Outperformance* is positive and highly significant, suggesting that analysts who perform better in forecasting green firms relative to non-green firms are more likely to achieve All-Star status.

Taken together, the evidence suggests that analysts' relative forecasting skill in green firms is associated with superior career outcomes. These findings imply that the reallocation of analysts' effort toward green firms, which occurs in the context of heightened EV salience, is beneficial for analysts' career advancement. Overall, EV salience appears to function as a cue of emerging trends rather than a source of distortion in analysts' forecasting focus..

7. Conclusion

This study examines how salient local cues of broader economic transition trends influence financial analysts' information processing and forecast accuracy. Using EV charging station deployment as a salient cue of the local green preference shift, we find that analysts exposed to higher local EV adoption significantly improve their forecast accuracy for green firms relative to non-green firms. Our analyses reveal that this improvement stems from a reallocation of analysts' limited attention rather than a net enhancement in overall forecasting ability. We find that analysts produce more frequent forecast revisions, ask more climate-related questions, and emphasize opportunity-oriented climate content in their reports on green firms when local EV salience is high. Instead of uniformly improving analysts' prediction capabilities, local EV salience prompts them to redirect cognitive resources toward environmentally friendly firms, potentially at the expense of attention to other companies.

The beneficial effects of EV salience on forecast accuracy are heterogeneous across both analysts and firms. Male, younger, and less-busy analysts exhibit greater responsiveness to local EV salience. At the firm level, the forecast accuracy improvement is more pronounced for green firms characterized by higher information asymmetry, where the marginal benefit of additional analyst attention is greater. These patterns are consistent with a selective attention reallocation mechanism, whereby local contextual cues guide analysts' efforts toward sustainability-aligned firms.

Our findings illuminate the profound interconnections between environmental technology advances and capital market dynamics. Beyond their direct impact on transportation and emissions reduction, investments in EV infrastructure generate valuable spillover effects by reshaping how financial intermediaries allocate attention and process information. As regulators around the world develop frameworks for climate finance and sustainable investment, our study underscores the importance of considering the potential spillover effects through which important green products and technologies can shape financial market information flows and support the broader low-carbon transition.

References

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets 5*(1), 31–56.

Babar, Y. and G. Burtch (2024). Recharging retail: Estimating consumer demand spillovers from electric vehicle charging stations. *Manufacturing & Service Operations Management 26*(3), 797–813.

Bae, K.-H., R. M. Stulz, and H. Tan (2008). Do local analysts know more? a cross-country study of the performance of local analysts and foreign analysts. *Journal of financial economics 88*(3), 581–606.

Bena, J., B. Bian, and H. Tang (2024). Financing the global shift to electric mobility. *Available at SSRN 4526150*.

Bordalo, P., N. Gennaioli, and A. Shleifer (2012). Salience theory of choice under risk. *The Quarterly journal of economics 127*(3), 1243–1285.

Bourveau, T., A. Garel, P. Joos, and A. Petit-Romec (2024). When attention is away, analysts misplay: distraction and analyst forecast performance. *Review of Accounting Studies 29*(1), 916–958.

Bradley, D., S. Gokkaya, and X. Liu (2017). Before an analyst becomes an analyst: Does industry experience matter? *The Journal of Finance 72*(2), 751–792.

Bushnell, J. B., E. Muehlegger, and D. S. Rapson (2022). Energy prices and electric vehicle adoption. Working Paper 29842, National Bureau of Economic Research.

Chan, J. (2024). Analysts' perspectives on climate change: An examination of analyst reports. *Available at SSRN 4890118*.

Chen, D., H. Li, Y. Ma, and R. Michaely (2025). Value, values, and opportunities in corporate environmental practices. *FEB-RN Research Paper* (108).

Chen, Q., W. J. Mayew, and H. Yan (2024). Equity analyst social interactions and geographic information transmission. *Review of Accounting Studies 29*(1), 327–353.

Clement, M. B. (1999). Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics 27*(3), 285–303.

Cox Automotive (2023). Tracking the momentum of ev adoption. Industry report, Cox Automotive, Atlanta, GA, USA.

Cuculiza, C., C. Antoniou, A. Kumar, and A. Maligkris (2021). Terrorist attacks, analyst sentiment, and earnings forecasts. *Management Science 67*(4), 2579–2608.

Davis, L. W., J. Li, and K. Springel (2025). Political ideology and u.s. electric vehicle adoption. *NBER Working Paper* (33591).

Derrien, F., P. Krueger, A. Landier, and T. Yao (2024). Esg news, future cash flows, and firm value. *Journal of Finance*. forthcoming.

Dhaliwal, D. S., S. Radhakrishnan, A. Tsang, and Y. G. Yang (2012). Nonfinancial disclosure and analyst forecast accuracy: International evidence on corporate social responsibility disclosure. *The accounting review 87*(3), 723–759.

Driskill, M., M. P. Kirk, and J. W. Tucker (2020). Concurrent earnings announcements and analysts' information production. *The Accounting Review 95*(1), 165–189.

Gerken, W. C. and M. O. Painter (2023). The value of differing points of view: Evidence from financial analysts' geographic diversity. *The Review of Financial Studies 36*(2), 409–449.

Gleason, C. A. and C. M. C. Lee. (2003). Analyst forecast revisions and market price discovery. *The Accounting Review 78*(1), 193–225.

Green, T. C., R. Jame, S. Markov, and M. Subasi (2014). Access to management and the informativeness of analyst research. *Journal of Financial Economics 114*(2), 239–255.

Han, Y., C. X. Mao, H. Tan, and C. Zhang (2024). Climatic disasters and distracted analysts. *Contemporary Accounting Research 41*(2), 1120–1150.

Harford, J., F. Jiang, R. Wang, and F. Xie (2019). Analyst career concerns, effort allocation, and firms' information environment. *The Review of Financial Studies 32*(6), 2179–2224.

Hirshleifer, D., Y. Levi, B. Lourie, and S. H. Teoh (2019). Decision fatigue and heuristic analyst forecasts. *Journal of Financial Economics 133*(1), 83–98.

Ioannou, I. and G. Serafeim (2015). The impact of corporate social responsibility on investment recommendations: Analysts' perceptions and shifting institutional logics. *Strategic Management Journal 36*(7), 1053–1081.

Klee, E., A. Morse, and C. Shin (2024). Auto finance in the electric vehicle transition. *Available at SSRN 4642783*.

Li, F. W. and B. Wang (2024). The gender effects of covid: evidence from equity analysts. *Review of Accounting Studies*.

Lim, T. (2001). Rationality and analysts' forecast bias. *The journal of Finance 56*(1), 369–385.

Loh, R. K. and R. M. Stulz (2018). Is sell-side research more valuable in bad times? *The journal of finance 73*(3), 959–1013.

Malloy, C. J. (2005). The geography of equity analysis. *The Journal of Finance 60*(2), 719–755.

O'Brien, P. C. and H. Tan (2015). Geographic proximity and analyst coverage decisions: Evidence from ipos. *Journal of Accounting and Economics 59*(1), 41–59.

Park, M., A. Yoon, and T. Zach (2024). Sell-side analysts' assessment of esg risk. *Available at SSRN 4211968*.

Peters, A. and E. Dütschke (2014). How do consumers perceive electric vehicles? a comparison of german consumer groups. *Journal of Environmental Policy & Planning 16*(3), 359–377.

Plötz, P., U. Schneider, J. Globisch, and E. Dütschke (2014). Who will buy electric vehicles? identifying early adopters in germany. *Transportation Research Part A: Policy and Practice 67*, 96–109.

Rapson, D. S. and E. Muehlegger (2023). The economics of electric vehicles. *Review of Environmental Economics and Policy 17*(2), 274–294.

Roger, T. (2024). Do financial analysts care about esg? *Finance Research Letters 63*, 105289.

Sautner, Z., L. Van Lent, G. Vilkov, and R. Zhang (2023). Firm-level climate change exposure. *The Journal of Finance 78*(3), 1449–1498.

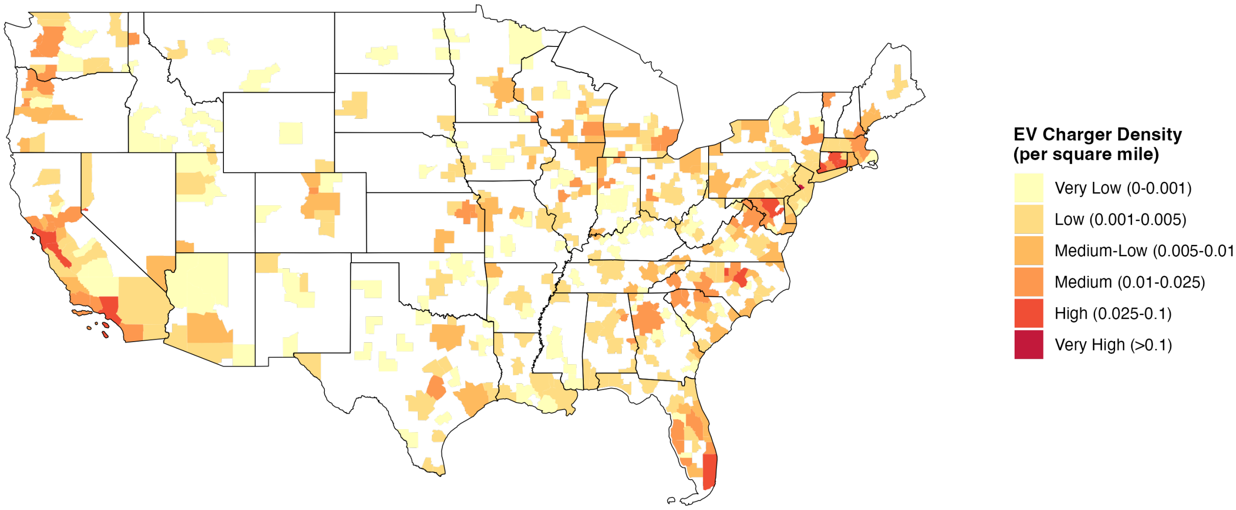
Sautner, Z., L. van Lent, G. Vilkov, and R. Zhang (2024). Climate value and values discovery. *Available at SSRN 4596668*.

Springel, K. (2021). Network externality and subsidy structure in two-sided markets: Evidence from electric vehicle incentives. *American Economic Journal: Economic Policy 13*(4), 393–432.

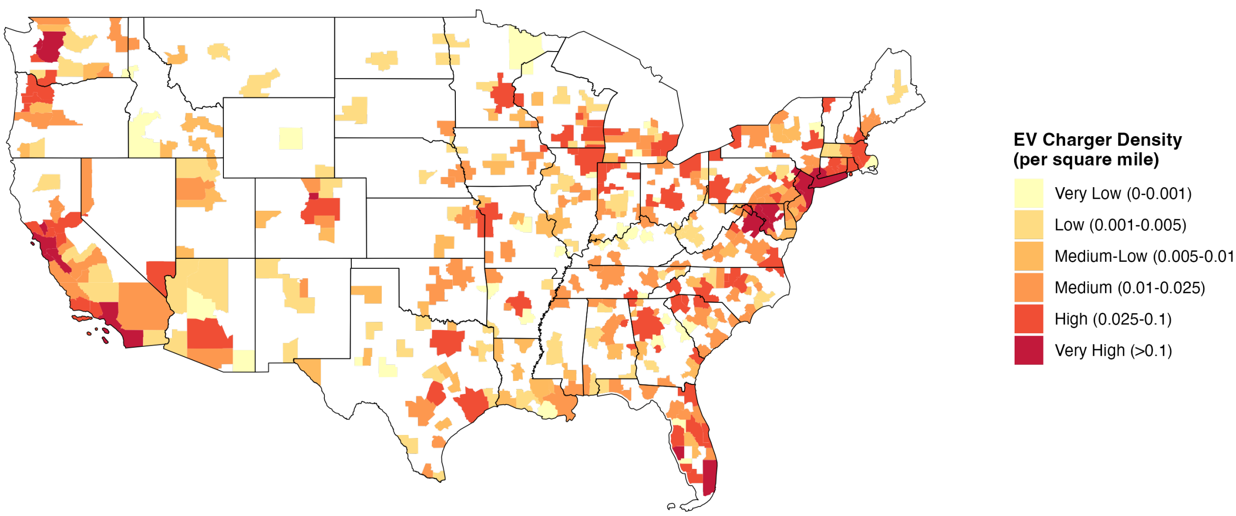
Union of Concerned Scientists and Consumer Reports (2022). Driving cleaner: Electric vehicles and infrastructure for communities of color. *Union of Concerned Scientists Report*. Available at https://www.ucsusa.org/resources/driving-cleaner.

Wooldridge, J. (2007). What's new in econometrics? lecture 10 difference-in-differences estimation. *NBER Summer Institute 9*(2011), 85.

Zheng, Y., D. R. Keith, S. Wang, M. Diao, and J. Zhao (2024). Effects of electric vehicle charging stations on the economic vitality of local businesses. *Nature Communications 15*(1), 7437.



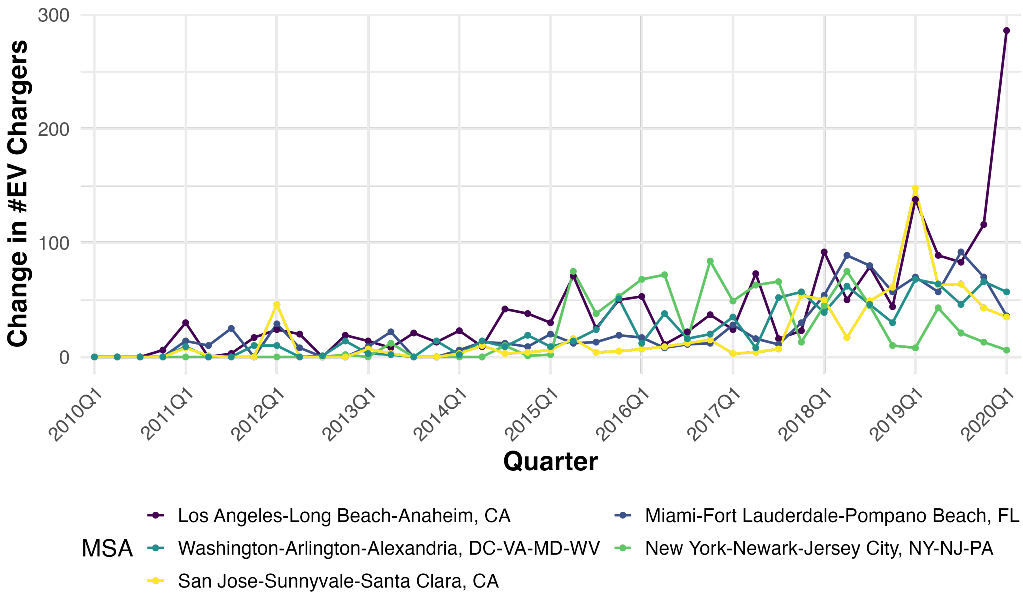
(a) EV Charger Density, 2015Q1



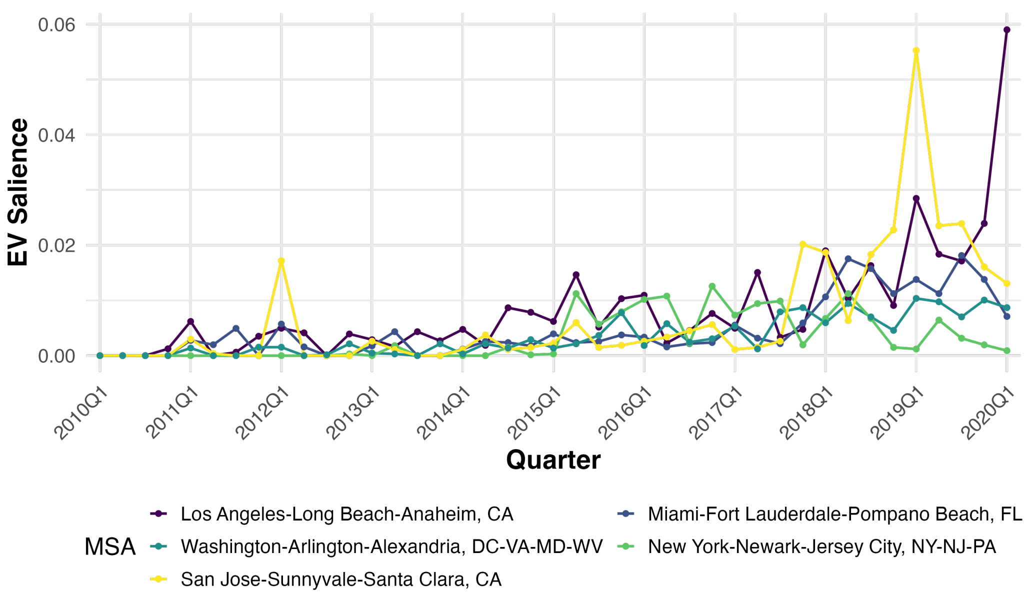
(b) EV Charger Density, 2020Q1

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).

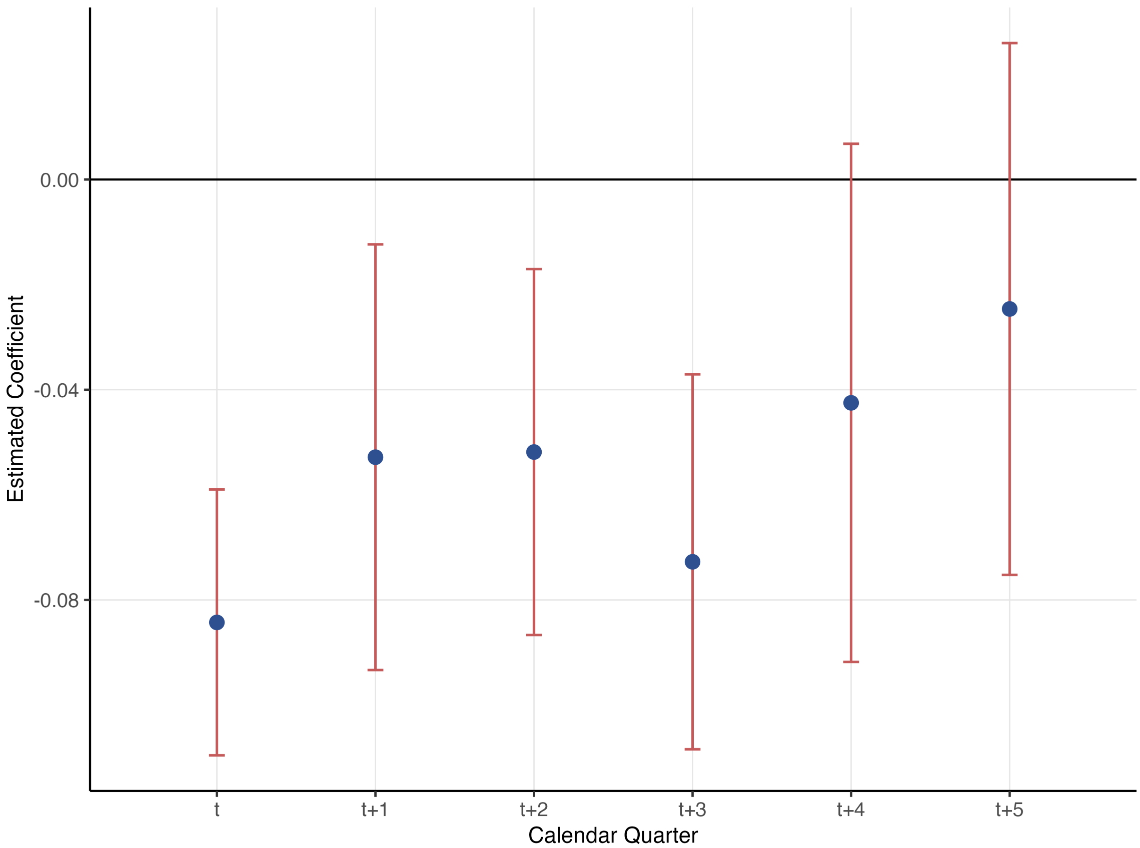


Figure 3. Long-Run Effects of EV Salience on Green Firm Forecast Accuracy

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. Quarter t represents the baseline quarter. Blue dots represent estimated coefficients, and red bars represent 95% confidence intervals. The regressions include firm × fiscal-quarter, analyst × 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. Baseline Regression: Forecast Error and EV Salience

Dep Var	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 on 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 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. *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 3. Does EV Salience Lead to Net Improvement in Forecast Accuracy?

Dep Var	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 on 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 MSAs. *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 4. Cross-Sectional Test (Analyst-Level)

Dep Var	Forecast Error					
	Male	Female	Young	Old	Non-Busy	Busy
	(1)	(2)	(3)	(4)	(5)	(6)
EV Salience × Green Firm	-0.0944***	0.6796	-0.0917**	-0.0340*	-0.1592***	-0.0456***
	(0.0130)	(0.4206)	(0.0345)	(0.0201)	(0.0559)	(0.0154)
Forecast Age	0.0004*	0.0009	0.0002	0.0008***	0.0007***	0.0007***
	(0.0002)	(0.0006)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Firm × Fiscal-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	237,775	9,342	89,561	131,624	68,004	179,330
Adj. R^2	0.886	0.932	0.885	0.879	0.899	0.878
F-test (p-value)	0.001		0.182		0.006	

This table reports cross-analyst heterogeneity tests on analysts' forecast accuracy. The regressions are on the forecast-analyst-firm-quarter level. Columns 1 and 2 divide the sample by the analyst's gender. Columns 3 and 4 divide the sample by the analyst's age, where "Young" refers to analysts whose age in 2015 was equal to or below the median, while "Old" refers to those above the median. Columns 5 and 6 divide the sample based on whether the analyst is classified as "Non-Busy" or "Busy", where "Busy" indicates that the number of firms the analyst covers in a given year is above the median, while "Non-Busy" refers to those at or below the median. 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 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. *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 5. Cross-Sectional Test (Firm-Level)

Dep Var	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 on 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 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 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. *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 6. EV Salience and Forecast Revision Rrequency

	(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 of the analyst's forecast revision frequency. The regressions are on the analyst-firm-quarter level. *Relative Frequency* is 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* is 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. *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. 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. 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 of the analyst's questions on climate issues. The regressions are on the analyst-quarter level. The data on analysts' climate questions is 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 at 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 in a conversation in the earnings call at 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 in a conversation in the earnings call at 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 MSAs, 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 8. Phrase Usage 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 on 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 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 MSAs, 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 9. 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 on 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 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. *Forecast Revision* is the difference between analyst i's current earnings forecast for firm j at time t 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 10. 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 on 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 11. Career Outcomes

Dep Var	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. Standard errors clustered at the firm level are reported in parentheses. ***, **, 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

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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 MSAs (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 current earnings forecast for firm j at time t 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 at 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 at 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 at 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					
Dep Var	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 U.S. 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

Dep Var	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

Dep Var	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.

Table A.5. Forecast Optimism and EV Salience

Dep Var	Forecast Optimism	
	(1)	(2)
EV Salience × Green Firm	-0.0055	-0.0142
	(0.0097)	(0.0183)
Forecast Age	0.0001	-0.0000
	(0.0001)	(0.0001)
Firm × Fiscal-Quarter FE	Yes	Yes
MSA × Year-Quarter FE	Yes	No
Analyst × Year-Quarter FE	No	Yes
Analyst × Firm FE	No	Yes
N	267,898	264,001
Adj. R^2	0.673	0.712

This table reports the results of analyst forecast optimism. The regressions are on the forecast-analyst-firm-quarter level. The dependent variable is *Forecast Optimism*, defined as the analyst's forecasted EPS minus the actual reported 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 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. *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.