

Expert financial communication and market response: Evidence from analyst recommendation actions in China

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Article

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Abstract

This study examines how expert financial communication is incorporated into market prices in China's equity market. Using 504,600 sell-side analyst-report events from July 2009 to March 2026, the analysis distinguishes static recommendation levels from vendor-defined recommendation actions, including upgrades, maintains, and downgrades. Recommendation actions predict subsequent market-adjusted returns more consistently than recommendation levels. In equal-weighted market-adjusted returns, the upgrade-minus-downgrade spread reaches 0.576 percentage points after one trading day and 3.001 percentage points after 63 trading days. The action effect remains robust to controls, fixed effects, and clustered inference, and is stronger among smaller and lower-coverage stocks. Forecast-fundamental revisions inside analyst-report forecast tables further reinforce recommendation actions and reveal hidden positive or negative information within Maintain reports. The evidence shows that expert financial communication transmits information unevenly across firms with different information environments.

JEL classification: *G14; G24; G12; C23.*

1. Introduction

Financial markets depend on expert intermediaries because information is costly to collect, interpret, and communicate. Sell-side analysts are one important group of such intermediaries. They gather firm-specific information, process public disclosures and market signals, produce research reports, and communicate their views through recommendation levels, recommendation actions, earnings forecasts, valuation metrics, and narrative analysis. We study analyst reports as expert financial communication events and ask how such communication is incorporated into market prices in China's equity market.

This question connects to broader research on costly information production, limited attention, disclosure processing, and market response. A central implication of this literature is that market prices need not immediately and uniformly reflect all available information when information acquisition, interpretation, and investor attention are costly (Grossman and Stiglitz, 1980; Hong and Stein, 1999; Bloomfield, 2002; Hirshleifer and Teoh, 2003; Barber and Odean, 2008; Da, Engelberg, and Gao, 2011; Lesmy, Muchnik, and Mugeran, 2025). In this setting, expert intermediaries can matter because they reduce information-processing costs and translate complex firm information into more observable signals. Analyst recommendations and recommendation revisions therefore provide a useful empirical setting for studying how expert communication enters market prices.

Prior research shows that analyst recommendations and recommendation revisions predict future stock returns. Stickel (1995) and Womack (1996) document market reactions to changes in analyst recommendations. Barber, Lehavy, McNichols, and Trueman (2001) show that portfolios based on recommendation levels can contain investment value. Boni and Womack (2006), Jegadeesh and Kim (2006), Moshirian, Ng, and Wu (2009), and Ryan and Taffler (2006) provide related evidence across industries, countries, and institutional settings. Related work also shows that analyst recommendations may reflect access incentives, career concerns, trade-generation motives, and heterogeneous communication to different investor clienteles (Hong and Kubik, 2003; Jackson, 2005; Chen and Matsumoto, 2006; Malmendier and Shanthikumar, 2014). We build on this literature by focusing on vendor-defined recommendation actions as observable changes in expert opinion rather than only on static recommendation levels.

Analyst communication is also multidimensional. Recommendation labels summarise analyst views, but they do not exhaust the information contained in analyst reports. Kecskés, Michaely, and Womack (2017) show that earnings estimate revisions can add value to recommendation changes, while Loh and Stulz (2018) show that sell-side research is especially valuable in bad times. Recent interdisciplinary work also examines analyst recommendation strategies and analyst forecasts as part of broader market-information processes (Vukovic et al., 2024; Fan and Zhang, 2024). China-focused studies further show that analyst information production and investor response depend on regulation, analyst characteristics, investor type, and investor preferences (Jiang, Lu, and Zhu, 2014; Kong et al., 2021; Liu et al., 2026; Li et al., 2026; Matsumoto, Zhang, and Zheng, 2026). Recent text-based work also shows that the narrative content of analyst reports contains investment-relevant information (Lv, 2025). We therefore examine not only headline recommendation actions, but also forecast-fundamental revisions inside analyst report forecast tables, allowing us to test whether the headline action is reinforced by the underlying report content.

China provides a useful setting for studying expert financial communication for three reasons. First, China's equity market is institutionally distinct from the developed markets in which much of the analyst-recommendation literature was developed. Prior research on China shows that analyst recommendation revisions contain information, while market frictions and short-sale constraints can affect how such information is incorporated into prices (Jiang, Lu, and Zhu, 2014). Second, investor composition is heterogeneous. Institutional and individual investors may differ in how they process analyst information, and investor information channels can also shape market behaviour (Kong et al., 2021; Zhou and Liu, 2022; Matsumoto, Zhang, and Zheng, 2026). Third, analyst coverage is uneven across firms, creating substantial cross-sectional variation in the information environment. This variation allows us to ask whether expert communication has stronger market effects among smaller and lower-coverage stocks, where information frictions are likely to be greater.

Our empirical design separates two related forms of analyst communication. The first is the recommendation level, which captures the analyst's current rating state. We code recommendation scores so that lower scores indicate more favourable opinions, and our main level comparison is Score1 minus Score3. The second is the recommendation action, which captures the direction of change in the analyst's communicated view. We classify vendor-defined actions into upgrades, maintains, and downgrades, and our main action comparison is upgrade minus downgrade. In additional confirmation tests, we combine recommendation actions with forecast-fundamental revisions from analyst-report forecast tables to examine whether headline actions are reinforced by changes in the underlying report content.

We find that recommendation actions provide a clearer and more stable measure of market-relevant expert communication than recommendation levels. In raw forward returns, the upgrade-minus-downgrade spread is 0.567 percentage points after one trading day, 1.099 percentage points after five trading days, 1.796 percentage points after 21 trading days, and 3.059 percentage points after 63 trading days. After subtracting the equal-weighted market benchmark return over the same horizon, the corresponding spread remains 0.576, 1.206, 1.802, and 3.001 percentage points. Upgrades outperform maintains across all horizons, while downgrades underperform maintains. Recommendation levels also contain information, but their simple market-adjusted return patterns are less stable, especially at intermediate and longer horizons.

We also show that the market response to analyst communication is stronger where information frictions are likely to be greater. Using firm size and prior analyst coverage as proxies for the information environment, we find that both recommendation-level effects and recommendation-action effects are generally stronger among smaller stocks and stocks with lower prior analyst coverage. This cross-sectional pattern is consistent with the view that expert communication matters more when public information is thinner and investors face greater information-processing frictions.

The results remain robust in formal regression and inference tests. Main regressions include report-year fixed effects, the log of lagged firm size, and the log of prior 365-day analyst coverage. The upgrade-minus-downgrade regression effect is 0.546 percentage points after one trading day and rises to 3.253 percentage points after 63 trading days, with t-statistics above 12 across all four horizons. The action effect remains statistically strong after absorbing report-month, stock, and broker fixed effects, and after clustering standard errors by stock, report date, and report month.

Finally, we show that forecast-fundamental revisions inside analyst reports internally validate recommendation actions. The confirmed action spread, which compares upgrades with favourable forecast-fundamental revisions to downgrades with unfavourable forecast-fundamental revisions, reaches 0.763 percentage points after one trading day and 3.708 percentage points after 63 trading days. Maintain reports also contain hidden information: Maintain reports with favourable forecast-fundamental revisions outperform Maintain reports with unfavourable revisions by 0.153, 0.413, 0.624, and 1.104 percentage points over the 1-, 5-, 21-, and 63-trading-day horizons, respectively. This evidence shows that analyst communication is multidimensional: headline recommendation actions matter, but the underlying forecast table also transmits market-relevant information.

We make three contributions. First, we contribute to research on expert financial communication by separating static recommendation levels from recommendation actions. Prior studies show that analyst recommendations and recommendation revisions predict stock returns, including event-study evidence on recommendation changes, portfolio evidence based on recommendation levels, and international evidence across institutional settings (Stickel, 1995; Womack, 1996; Barber, Lehavy, McNichols, and Trueman, 2001; Jegadeesh and Kim, 2006; Moshirian, Ng, and Wu, 2009). We build on this literature by treating vendor-defined recommendation actions as observable changes in communicated expert opinion, rather than as minor variants of

recommendation levels. This distinction is empirically important. Recommendation levels summarise the analyst's current rating state, while upgrades and downgrades reveal changes in that state. Our evidence shows that recommendation actions provide a cleaner and more stable measure of market-relevant expert communication than static recommendation levels.

Second, we contribute to research on information frictions in China and other institutionally distinctive markets. Jiang, Lu, and Zhu (2014) show that analyst recommendation revisions contain information in the Chinese stock market and emphasise the role of market frictions and short-sale constraints. Kong et al. (2021) show that institutional and individual investors trade differently on analyst recommendations, while recent studies examine regulatory, analyst-characteristic, investor-preference, and textual dimensions of analyst research in China (Liu et al., 2026; Li et al., 2026; Matsumoto, Zhang, and Zheng, 2026; Lv, 2025). We add to this literature by linking the market response to analyst communication directly to the firm's information environment. Using a large and recent sample of 504,600 analyst-report events from July 2009 to March 2026, we show that recommendation effects are stronger among smaller stocks and stocks with lower prior analyst coverage. This evidence connects expert communication to the uneven information environments faced by different firms.

Third, we contribute by showing that analyst communication is multidimensional. Recommendation actions are useful headline signals, but they do not exhaust the information contained in analyst reports. We therefore link headline recommendation actions to forecast-fundamental revisions inside analyst-report forecast tables. This design allows us to test whether the headline action is supported by changes in the underlying forecast information. The evidence shows that the most informative recommendation actions are those accompanied by favourable or unfavourable forecast-fundamental revisions. It also shows that Maintain reports, despite having unchanged headline recommendations, can contain hidden positive or negative information when the underlying forecast table changes. Our results therefore connect headline expert signals with the richer informational content embedded in the same communication event.

We proceed as follows. Section 2 describes the data, variables, and event-return alignment. Section 3 presents hypotheses and empirical specifications. Section 4 reports baseline evidence on market response and information-asymmetry patterns. Section 5 presents regression evidence, robustness tests, and forecast-fundamental confirmation tests. Section 6 discusses the broader implications for expert financial communication and information frictions. Section 7 concludes.

2. Data and variable construction

2.1 Analyst-event sample

We obtain analyst recommendation data from the iFinD financial data terminal provided by Hithink RoyalFlush Information Network Co., Ltd. iFinD integrates capital-market information resources and provides financial data and information services to a broad user base, including government agencies, firms, intermediaries, media organisations, investors, and other users. We treat each analyst report as an expert communication event associated with a specific stock and report date. The full sample contains 504,600 analyst-report events from July 13, 2009 to March 28, 2026. The recommendation-level event-aligned sample contains 399,348 observations, and the recommendation-action event-aligned sample contains 350,989 observations.

The sample is broad but not uniform across firm types. There are 478,788 rows with valid size-bucket assignment and 488,987 rows with valid prior-coverage-bucket assignment. Large-stock events account for 310,771 observations, or 61.6% of the sample. Mid-size-stock events account for 124,039 observations, or 24.6%. Small-stock events account for 43,978 observations, or 8.7%. This distribution reflects the familiar fact that analyst coverage is tilted toward larger firms, which makes heterogeneity by size an important part of our empirical design.

Prior analyst coverage is also heterogeneous. Low-prior-coverage, mid-prior-coverage, and high-prior-coverage buckets contain 146,690, 195,592, and 146,705 events, respectively. Mean prior coverage is 7.1 reports in the low-coverage bucket, 23.2 reports in the mid-coverage bucket, and 48.4 reports in the high-coverage bucket. We use this variation to test whether expert communication has stronger market effects when prior analyst attention is thinner.

The event-level structure is important for our empirical design. The unit of analysis is not a firm-month or firm-year panel, but an analyst-report event panel that preserves the timing of expert communication. This structure allows us to align subsequent returns

to the release of analyst information and to compare market responses across recommendation levels and recommendation actions. It also allows multiple analyst reports on the same stock to enter the sample when they occur on different report dates, reflecting the information flow that investors observe in real time.

Because analyst coverage is not randomly assigned across stocks, we treat sample composition as an empirical feature rather than as a nuisance. Larger and more visible firms naturally attract more analyst reports, while smaller and less frequently covered firms provide a useful setting for testing whether analyst communication matters more when information frictions are greater. The size and prior-coverage distributions reported in Table 1 therefore serve two purposes: they describe the composition of the event sample, and they motivate our cross-sectional tests of information asymmetry.

2.2 Forward returns and market adjustment

For each analyst-report event, we compute forward stock returns over 1, 5, 21, and 63 trading days. These horizons capture immediate market response, short-term post-event adjustment, one-month continuation, and approximately one-quarter continuation. The baseline raw-return tests compare market responses across recommendation levels and recommendation actions.

We use multiple horizons to distinguish immediate price reaction from more persistent post-event information incorporation. A 1-trading-day horizon captures the market reaction shortly after the analyst communication becomes tradable information. The 5-trading-day horizon captures short-term adjustment over approximately one trading week. The 21-trading-day horizon corresponds approximately to one trading month, while the 63-trading-day horizon corresponds approximately to one trading quarter. If analyst actions convey information that is not fully incorporated immediately, the return response should persist beyond the first trading day. Conversely, if the market fully incorporates analyst information immediately, longer-horizon responses should weaken or disappear.

Our main adjusted dependent variable subtracts the EW market benchmark return over the same horizon. Let $\text{RawRet}_{i,t,h}$ denote the forward stock return for event i on date t over horizon h , and let $\text{EWMarketRet}_{t,h}$ denote the EW market return over the same horizon. The EW market-adjusted return is $\text{EWAdjRet}_{i,t,h} = \text{RawRet}_{i,t,h} - \text{EWMarketRet}_{t,h}$. All coefficients in the empirical tables are reported in percentage points, with t-statistics in parentheses.

The equal-weighted market adjustment provides a simple benchmark for broad market movements. This adjustment is useful in an event-level design because analyst reports may cluster in periods when market-wide returns are unusually high or low. Without market adjustment, a return response could partly reflect the timing of analyst-report activity rather than the information content of the analyst communication itself. By subtracting the contemporaneous equal-weighted market return over the same horizon, the adjusted return focuses on stock-level performance relative to the average market movement during the event window. We align forward returns to begin after the analyst report becomes tradable information. For reports released after market close or outside trading hours, we align the event to the next trading day.

2.3 Recommendation levels and recommendation actions

We code recommendation levels so that lower scores indicate more favourable analyst opinions. The principal level comparison is Score1 minus Score3. In regression specifications, Score3 serves as the omitted recommendation-level category; therefore, the Score1 coefficient measures the return difference between the most favourable level and the neutral level after controls and fixed effects.

We classify recommendation actions using the vendor-defined direction of adjustment. We group events into upgrades, maintains, and downgrades. Maintain is the omitted category in action regressions. The upgrade coefficient measures the return difference between upgrades and maintains. The downgrade coefficient measures the return difference between downgrades and maintains. Our central action effect is the upgrade-minus-downgrade contrast.

The distinction between levels and actions is central to our paper. Recommendation levels measure the analyst's current rating state, while recommendation actions measure the direction of change in that state. A stock can receive a favourable recommendation level without a new upgrade if the analyst has been favourable for some time. Similarly, an upgrade may occur

even when the final recommendation level is not the most favourable category. Comparing recommendation levels with recommendation actions therefore allows us to distinguish static expert opinions from communicated revisions in expert views.

2.4 Forecast-fundamental revisions

In additional confirmation tests, we use forecast information from analyst-report forecast tables. This information includes analyst forecasts of next-fiscal-year earnings and growth, as well as price-scaled forecast-fundamental measures such as forward price-to-earnings ratios and price/earnings-to-growth (PEG) ratios. These variables allow us to examine whether headline recommendation actions are reinforced by the underlying forecast information contained in the same analyst report.

Our key auxiliary signal is the forecast-fundamental revision. It measures whether the price-scaled forecast fundamentals in the current report have become more or less favourable relative to the prior forecast information available for the same stock. We interpret a favourable forecast-fundamental revision as indicating that the stock has become more attractive relative to analyst-forecast fundamentals, while an unfavourable forecast-fundamental revision indicates that it has become less attractive. Economically, this signal captures changes in the relationship between the current stock price and analyst-forecast earnings and growth.

We combine this revision signal with headline recommendation actions to construct forecast-confirmation tests. A confirmed positive action refers to an upgrade accompanied by a favourable forecast-fundamental revision. A confirmed negative action refers to a downgrade accompanied by an unfavourable forecast-fundamental revision. We also compare Maintain reports with favourable versus unfavourable forecast-fundamental revisions to test whether unchanged headline recommendations contain hidden positive or negative information. These tests help us assess whether analyst communication is internally consistent across the headline recommendation action and the forecast information inside the same report.

2.5 Information-asymmetry proxies

We use two conditioning variables to test whether analyst communication has stronger market effects in stocks subject to greater information asymmetry. The first is stock size. Small stocks are less heavily followed by investors and analysts, and firm-specific information may be more costly to process. The second is prior analyst coverage over the previous 365 days. Stocks with lower prior analyst coverage should have thinner public information environments and therefore provide more room for analyst reports to add incremental information.

Our empirical tests compare small stocks with large stocks and low-prior-coverage stocks with high-prior-coverage stocks. We report the heterogeneity estimates as difference-in-differences (DID) effects. Positive estimates indicate that the analyst signal is stronger in the higher-information-friction group.

These proxies are intentionally transparent. Firm size is a standard proxy for the richness of the information environment because larger firms typically receive more investor attention, media coverage, and institutional monitoring. Prior analyst coverage captures the recent intensity of sell-side information production for the same stock. A low-prior-coverage stock is not necessarily neglected, but it has received less recent analyst attention than a high-prior-coverage stock. If recommendation actions reveal incremental expert information, the upgrade-minus-downgrade effect should be stronger among smaller and lower-coverage stocks.

3. Methods: hypotheses and empirical specifications

Our first hypothesis concerns recommendation levels. If favourable recommendation levels convey useful information about firm prospects, valuation, or investor demand, stocks receiving the most favourable recommendation level should experience stronger subsequent market responses than neutral recommendation stocks. The level effect should be positive in raw returns and should remain positive after controlling for broad market movements and observable firm-level conditions.

This hypothesis is based on the idea that recommendation levels aggregate the analyst's assessment of firm value, expected performance, valuation, and investment attractiveness. A more favourable recommendation level may therefore summarise expert information that is not yet fully reflected in prices. At the same time, recommendation levels may also contain persistent analyst optimism or slow-moving coverage-selection effects. For this reason, we compare recommendation levels both in simple return spreads and in regressions that control for firm size, prior analyst attention, and time effects.

Hypothesis 1

(H1). *More favourable recommendation levels predict stronger subsequent stock returns. The primary level effect is Score1 minus Score3.*

Our second hypothesis concerns recommendation actions. Actions may be especially informative because they summarise changes in analyst views. An upgrade indicates an improvement relative to the analyst's prior opinion or the vendor's prior rating state. A downgrade indicates a deterioration in analyst opinion. If actions capture revisions in expert information, upgrades should be followed by stronger market responses than downgrades.

This hypothesis emphasises changes in analyst views rather than the level of analyst optimism. The distinction is important because revisions are more likely to contain incremental information relative to what investors already know. An upgrade may reveal improved expectations, new favourable information, or a reassessment of valuation, while a downgrade may reveal deteriorating expectations or unfavourable new information. Therefore, the upgrade-minus-downgrade contrast is our central empirical object for testing whether analyst actions contain market-relevant information.

Hypothesis 2

(H2). *Analyst upgrades predict higher future stock returns than analyst downgrades. The primary action effect is Upgrade minus Downgrade.*

Our third hypothesis concerns information asymmetry. If expert communication reduces information frictions, then recommendation signals should be stronger where information asymmetry is more severe. We test this prediction using size and prior analyst coverage.

H3 links market response to the information environment. Smaller stocks and lower-coverage stocks are expected to have thinner public information environments, lower investor attention, and greater information-processing frictions. If analyst reports reduce these frictions, the same recommendation signal should have a larger effect in these stocks than in large or heavily covered stocks. We therefore compare signal effects across size and prior-coverage groups using difference-in-differences estimates.

Hypothesis 3

(H3). *Recommendation-level and recommendation-action effects are stronger among smaller stocks and among stocks with lower prior analyst coverage.*

The baseline recommendation-level regression is

$$EWAdjRet_{i,t,h} = \alpha_h + \beta_{1,h}Score1_{i,t} + \beta_{2,h}Score2_{i,t} + \beta_{4,h}Score4_{i,t} + \beta_{5,h}Score5_{i,t} + \gamma'_h X_{i,t} + \delta_{year(t)} + \epsilon_{i,t,h}. \quad (1)$$

where Score3 is the omitted category and X includes the log of lagged firm size and the log of prior 365-day analyst coverage.

The baseline recommendation-action regression is

$$EWAdjRet_{i,t,h} = \alpha_h + \theta_{U,h}Upgrade_{i,t} + \theta_{D,h}Downgrade_{i,t} + \gamma'_h X_{i,t} + \delta_{year(t)} + \epsilon_{i,t,h}. \quad (2)$$

where Maintain is omitted. The key action effect is $\theta_{U,h} - \theta_{D,h}$.

The coefficient interpretation follows directly from the omitted categories. In the recommendation-level regression, the Score1 coefficient measures the average return difference between the most favourable recommendation level and the neutral category, conditional on the included controls and fixed effects. In the recommendation-action regression, the upgrade coefficient measures the return difference between upgrades and maintains, while the downgrade coefficient measures the return difference between downgrades and maintains. We obtain the upgrade-minus-downgrade effect by taking the difference between these two action coefficients. A positive and statistically significant upgrade-minus-downgrade effect indicates that analyst actions contain predictive information beyond the maintain benchmark.

To test H3, we estimate interacted versions of the baseline specifications. We use the interaction terms to compare the recommendation effect in high-information-friction groups with the corresponding effect in low-information-friction groups. For size, our main comparison is small stocks minus large stocks. For prior analyst coverage, our main comparison is low-prior-coverage stocks minus high-prior-coverage stocks. Positive interaction estimates indicate that the recommendation signal is stronger among stocks with greater information frictions.

We assess robustness using alternative fixed effects and standard-error assumptions. Fixed-effect specifications replace report-year fixed effects with report-month, stock, or broker fixed effects. Report-month fixed effects absorb common time shocks at a finer frequency than report-year fixed effects. Stock fixed effects compare recommendation signals within the same stock over time, reducing concern that the results are driven by persistent differences across firms. Broker fixed effects absorb persistent broker-level differences in rating style, optimism, and coverage universe. Additional inference tests use stock clustering, report-date clustering, and report-month clustering, allowing residual correlation within firms and within common event-time groups.

Statistical inference is based on two-sided tests. We report coefficients and return spreads in percentage points, with t-statistics in parentheses. Unless otherwise stated, statistical significance is assessed at the 10%, 5%, and 1% levels and indicated by *, **, and ***, respectively. Baseline regressions use heteroskedasticity-consistent standard errors, and robustness tests report standard errors clustered by stock, report date, or report month. The relevant event-aligned sample sizes are reported in Table 1 and vary across tests depending on data availability.

4. Baseline empirical evidence

This section presents the baseline evidence in three steps. We first summarise the analyst-report event sample and the conditioning variables used in the heterogeneity tests. We then compare raw forward returns across recommendation levels and recommendation actions. Finally, we examine equal-weighted market-adjusted returns and information-asymmetry bucket tests. This sequence addresses three empirical questions: whether analyst communication is followed by differential market responses in simple event-time comparisons, whether these responses survive adjustment for broad market movements, and whether they are stronger where information frictions are likely to be greater.

4.1 Data summary

Table 1 summarises the empirical sample. The sample contains more than half a million analyst-report events over a long post-2009 period. The event-aligned samples are smaller because return construction, recommendation-level classification, and recommendation-action classification require complete information. The conditioning variables show substantial variation in firm size and prior analyst coverage, supporting our cross-sectional tests of information asymmetry.

Table 1

Data summary This table summarises the analyst-report event sample used in the empirical analysis. The full sample contains all analyst-report events from July 13, 2009 to March 28, 2026. The recommendation-level and recommendation-action event-aligned samples are smaller because return construction and signal classification require complete information. Size buckets and prior-coverage buckets are used in the information-asymmetry tests. Prior analyst coverage is measured as the number of analyst reports issued for the same stock over the previous 365 days.

Sample item	Value
Full analyst-event observations	504,600
Sample period	2009-07-13 to 2026-03-28
Recommendation-level event-aligned sample	399,348
Recommendation-action event-aligned sample	350,989
Rows with valid size bucket	478,788
Rows with valid prior-coverage bucket	488,987
Large-stock events	310,771 (61.6%)
Mid-size-stock events	124,039 (24.6%)
Small-stock events	43,978 (8.7%)
Low prior-coverage events	146,690 (29.1%)
Mid prior-coverage events	195,592 (38.8%)
High prior-coverage events	146,705 (29.1%)
Mean prior coverage: Low / Mid / High	7.1 / 23.2 / 48.4 reports

4.2 Raw-return evidence

Table 2 reports the baseline raw-return spreads. The raw-return evidence shows that both recommendation levels and recommendation actions are followed by differential market responses. The Score1-minus-Score3 spread is 0.292 percentage points after one trading day, 0.642 percentage points after five trading days, 0.412 percentage points after 21 trading days, and 1.766 percentage points after 63 trading days. Each estimate is statistically significant.

Table 2

Raw-return evidence This table reports raw forward return spreads following analyst recommendation signals. Forward returns are measured over 1, 5, 21, and 63 trading days after the analyst report becomes tradable information. Recommendation-level effects compare favourable recommendation categories with less favourable or neutral categories. Recommendation-action effects compare upgrades, maintains, and downgrades based on vendor-defined action labels. Each entry is reported in percentage points, with the t-statistic in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Effect	1d	5d	21d	63d
Score1 - Score3	0.292*** (11.15)	0.642*** (10.90)	0.412*** (3.00)	1.766*** (9.23)
Score1 - Score2	0.103*** (8.01)	0.289*** (11.38)	0.381*** (8.15)	0.373*** (4.61)
Favourable - Neutral	0.253*** (9.86)	0.531*** (9.13)	0.266* (1.95)	1.623*** (8.60)
Upgrade - Maintain	0.336*** (9.16)	0.467*** (6.55)	0.802*** (6.05)	1.181*** (5.25)
Downgrade - Maintain	-0.231*** (-8.23)	-0.632*** (-10.37)	-0.995*** (-8.51)	-1.879*** (-9.07)
Upgrade - Downgrade	0.567*** (12.45)	1.099*** (11.91)	1.796*** (10.32)	3.059*** (10.19)

The action evidence is stronger and more monotonic. Upgrades outperform maintains by 0.336, 0.467, 0.802, and 1.181 percentage points over the 1-, 5-, 21-, and 63-day horizons. Downgrades underperform maintains by 0.231, 0.632, 0.995, and 1.879 percentage points. As a result, the upgrade-minus-downgrade spread is 0.567, 1.099, 1.796, and 3.059 percentage points across the four horizons, with t-statistics between 10.19 and 12.45. The raw-return evidence therefore identifies recommendation actions as a strong communication signal associated with subsequent market performance.

The monotonic ordering across upgrades, maintains, and downgrades is important for interpretation. If the result were driven only by a small subset of extreme observations or by a generic positive tone in analyst reports, we would not necessarily expect both sides of the action classification to move in opposite directions around the maintain category. Instead, upgrades are followed by higher returns than maintains, while downgrades are followed by lower returns than maintains. This pattern suggests that the vendor-defined action label captures economically meaningful information about the direction of communicated analyst revisions.

4.3 Equal-weighted market-adjusted evidence

Table 3 reports returns after subtracting the EW market return over the same horizon. This adjustment matters because analyst-report activity may cluster in market states when broad returns are unusually high or low. After market adjustment, the recommendation-action result remains strong. Upgrades outperform maintains at every horizon, while downgrades underperform maintains at every horizon. The upgrade-minus-downgrade spread is 0.576 percentage points after one trading day, 1.206 after five trading days, 1.802 after 21 trading days, and 3.001 after 63 trading days. All four estimates are highly statistically significant. Figure 1 plots the corresponding market-adjusted response to analyst recommendation actions across horizons.

Table 3

Equal-weighted market-adjusted return evidence This table reports equal-weighted (EW) market-adjusted forward return spreads. For each event and horizon, the EW market return over the same event window is subtracted from the stock's forward return. This adjustment removes broad market movements that may coincide with analyst-report activity. The table compares recommendation-level effects and recommendation-action effects over 1-, 5-, 21-, and 63-trading-day horizons. Each entry is reported in percentage points, with the t-statistic in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Effect	1d	5d	21d	63d
Score1 - Score2	0.07*** (5.42)	0.06*** (2.65)	-0.20*** (-4.75)	-0.37*** (-5.05)
Score1 - Score3	0.20*** (8.71)	0.19*** (3.67)	-0.74*** (-5.81)	-0.09 (-0.51)
Upgrade - Maintain	0.36*** (10.46)	0.85*** (12.84)	1.46*** (12.19)	1.92*** (9.52)
Downgrade - Maintain	-0.21*** (-8.42)	-0.36*** (-6.83)	-0.34*** (-3.40)	-1.08*** (-6.05)
Upgrade - Downgrade	0.58*** (13.60)	1.21*** (14.51)	1.80*** (11.73)	3.00*** (11.35)

This figure plots equal-weighted (EW) market-adjusted forward return spreads for analyst recommendation actions. For each event and horizon, the EW market return over the same event window is subtracted from the stock's forward return. The figure highlights the upgrade-minus-downgrade spread over 1-, 5-, 21-, and 63-trading-day horizons, corresponding to the action evidence in Table 3.

The recommendation-level result is more nuanced. Score1 outperforms Score2 at the 1- and 5-day horizons but underperforms at the 21- and 63-day horizons in this simple adjusted-return comparison. Score1 outperforms Score3 over 1 and 5 days, but the 21-day and 63-day estimates are negative. This pattern does not eliminate the level signal in formal regressions, but it shows that static recommendation levels are less stable than recommendation actions once broad market returns are removed.

The difference between recommendation levels and recommendation actions is sharper after market adjustment. Recommendation levels may partly reflect persistent optimism toward firms that analysts already view favourably, and such firms may be exposed to common market movements or time-varying investor sentiment. Recommendation actions, by contrast, capture revisions in analyst views and therefore appear less sensitive to the market-adjustment choice. The persistence of the upgrade-minus-downgrade spread after subtracting the EW market return provides evidence that analyst actions convey stock-level information rather than merely reflecting broad market conditions.

4.4 Information-asymmetry bucket tests

Table 4 reports DID estimates by size and prior coverage. For size, we compare small stocks with large stocks. For prior coverage, we compare low-prior-coverage stocks with high-prior-coverage stocks. Positive estimates indicate stronger analyst-signal effects where information frictions are expected to be greater. Figures 2 and 3 summarise the corresponding size and prior-coverage heterogeneity patterns for analyst-action effects.

Table 4

Information-asymmetry tests This table reports difference-in-differences (DID) estimates for information-asymmetry tests. The size test compares the analyst-signal effect among small stocks with the corresponding effect among large stocks. The coverage test compares the analyst-signal effect among stocks with low prior analyst coverage with the corresponding effect among stocks with high prior analyst coverage. Prior analyst coverage is measured over the previous 365 days. Positive estimates indicate that the recommendation signal is stronger among stocks with greater information frictions. Each entry is reported in percentage points, with the t-statistic in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Effect	1d	5d	21d	63d
Small - Large: Score1 - Score3	0.43*** (5.99)	0.86*** (5.11)	2.15*** (6.58)	1.77*** (3.36)
Small - Large: Upgrade - Downgrade	0.44*** (3.02)	1.82*** (4.68)	2.17*** (3.05)	1.88* (1.84)
Low - High Coverage: Score1 - Score3	0.28*** (4.48)	0.41*** (3.07)	0.69** (2.06)	0.07 (0.17)
Low - High Coverage: Upgrade - Downgrade	0.24** (2.00)	0.67*** (3.01)	1.05** (2.57)	2.05*** (2.97)

This figure plots the upgrade-minus-downgrade effect across firm-size buckets. The comparison illustrates whether analyst-action return predictability is stronger among smaller stocks than among larger stocks. The pattern corresponds to the size-based information-asymmetry tests reported in Table 4.

This figure plots the upgrade-minus-downgrade effect across prior analyst coverage buckets. Prior coverage is measured using the number of analyst reports issued for the same stock over the previous 365 days. The comparison illustrates whether analyst-action return predictability is stronger among stocks with lower prior analyst coverage, corresponding to the coverage-based information-asymmetry tests reported in Table 4.

The size tests support the information-asymmetry interpretation. The small-minus-large difference for the Score1-minus-Score3 effect is positive at all horizons, ranging from 0.434 percentage points after one trading day to 2.154 percentage points after 21 trading days. The small-minus-large difference for the upgrade-minus-downgrade effect is also positive across horizons, including 1.825 percentage points after five trading days and 2.168 percentage points after 21 trading days.

The prior-coverage tests point in the same direction. The low-minus-high coverage difference for the upgrade-minus-downgrade effect is 0.237 percentage points after one trading day, 0.670 after five trading days, 1.046 after 21 trading days, and 2.050 after 63 trading days. These estimates indicate that recommendation actions have stronger market effects for stocks with thinner prior analyst attention. These findings support H3, which predicts stronger recommendation effects among stocks with greater information frictions.

The heterogeneity results also help distinguish the information-asymmetry interpretation from a pure attention or mechanical return-drift explanation. If analyst actions simply proxy for broad market sentiment, their effects should not necessarily be stronger among smaller or lower-coverage stocks. Larger effects in these groups are more consistent with the view that analyst reports are more informative when investors have less prior information. This evidence is therefore consistent with an information-friction interpretation of the baseline market-response patterns.

5. Regression evidence and robustness

This section evaluates whether the baseline market-response patterns survive more formal regression designs and whether recommendation actions are reinforced by forecast-fundamental revisions. The baseline spread tests are useful because they are transparent and directly interpretable, but they do not fully address observable differences across firms, time variation in market conditions, or dependence in event-level residuals. We use the tests in this section for four purposes. First, we examine whether

recommendation levels and recommendation actions predict EW market-adjusted returns after controlling for firm size, prior analyst coverage, and report-year conditions. Second, we test whether the results are robust to alternative fixed-effect structures that absorb time-, stock-, and broker-level heterogeneity. Third, we examine whether statistical significance is robust to different clustering assumptions. Fourth, we test whether forecast-fundamental revisions inside the same analyst report internally validate recommendation actions.

5.1 Main regression evidence

Table 5 reports the main regression estimates using EW market-adjusted returns as the dependent variable. The regressions include report-year fixed effects, the log of lagged firm size, and the log of prior 365-day analyst coverage. This design tests whether analyst communication is associated with differential market responses after accounting for basic differences in firm size, prior attention, and report-year conditions.

Table 5

Main regression evidence This table reports the main regression estimates using equal-weighted (EW) market-adjusted forward returns as the dependent variable. H1 estimates are based on Eq. (1), where Score3 is the omitted recommendation-level category. H2 estimates are based on Eq. (2), where Maintain is the omitted recommendation-action category. The heterogeneity rows are estimated from corresponding interacted versions of Equations (1) and (2), using size and prior analyst coverage as conditioning variables. Regressions include report-year fixed effects and controls for the log of lagged firm size and the log of prior 365-day analyst coverage. Each entry is reported in percentage points, with the t-statistic in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Model / Effect	1d	5d	21d	63d
H1: Score1 - Score3	0.26*** (11.02)	0.52*** (10.07)	0.46*** (4.48)	2.09*** (12.25)
H2: Upgrade - Downgrade	0.55*** (15.29)	1.22*** (15.27)	1.90*** (12.57)	3.25*** (12.45)
Size DID: Small - Large, Score1 - Score3	0.35*** (4.90)	0.66*** (3.94)	1.59*** (4.91)	0.80 (1.54)
Size DID: Small - Large, Upgrade - Downgrade	0.43*** (2.91)	1.76*** (4.52)	2.01*** (2.84)	1.56 (1.53)
Coverage DID: Low - High, Score1 - Score3	0.28*** (4.87)	0.54*** (4.35)	1.71*** (6.79)	1.28*** (3.17)
Coverage DID: Low - High, Upgrade - Downgrade	0.16* (1.73)	0.58*** (2.77)	0.84** (2.12)	2.00*** (2.93)

The H1 level effect is positive in the regression framework. The Score1-minus-Score3 coefficient is 0.259 percentage points at the 1-day horizon, 0.519 at the 5-day horizon, 0.463 at the 21-day horizon, and 2.091 at the 63-day horizon. The corresponding t-statistics are 11.02, 10.07, 4.48, and 12.25. Thus, recommendation levels retain predictive content in formal regressions even though the simple market-adjusted return spreads are less stable at longer horizons.

The H2 action effect is our strongest result. The upgrade-minus-downgrade coefficient is 0.546 percentage points after one trading day, 1.221 after five trading days, 1.899 after 21 trading days, and 3.253 after 63 trading days. The t-statistics are 15.29, 15.27, 12.57, and 12.45. These estimates show that recommendation actions contain economically large and statistically robust market-relevant information beyond the control variables and report-year fixed effects. Figure 4 plots the baseline regression effects across horizons.

The regression evidence reinforces the central distinction between recommendation levels and recommendation actions. The recommendation-level effect is positive in the baseline regressions, but the action effect is larger and more stable across

horizons. This pattern is consistent with the view that changes in analyst views contain more incremental information than the level of analyst optimism alone. The magnitude of the action effect is also economically meaningful. A 3.253 percentage-point upgrade-minus-downgrade difference over 63 trading days is large relative to the horizon and indicates that analyst actions capture more than a short-lived announcement reaction.

This figure summarises the main regression effects for recommendation levels and recommendation actions. The recommendation-level effect is measured as Score1 minus Score3, and the recommendation-action effect is measured as Upgrade minus Downgrade. The dependent variable is the equal-weighted (EW) market-adjusted forward return. The figure corresponds to the main regression estimates reported in Table 5.

The regression-based heterogeneity estimates also support the information-asymmetry channel. Size DID estimates are positive for both Score1-minus-Score3 and upgrade-minus-downgrade effects. Coverage DID estimates are also positive, particularly at the 21- and 63-day horizons. Together, these interactions indicate that analyst communication has stronger market effects where information frictions are plausibly higher.

These regression-based heterogeneity results complement the bucket tests in Section 4.4. The bucket tests provide a transparent comparison across size and coverage groups, while the interacted regressions show that the same pattern remains after controlling for firm size, prior analyst coverage, and report-year effects. This consistency strengthens the interpretation that the market-response patterns are related to information frictions rather than only to unconditional differences across stocks.

5.2 Fixed-effect robustness

Table 6 tests robustness to alternative fixed effects. Panel A reports the recommendation-level effect, and Panel B reports the recommendation-action effect. Report-month fixed effects absorb common time shocks at a finer frequency than report-year fixed effects. Stock fixed effects compare analyst signals within the same stock over time and therefore reduce concern that the result is driven by persistent differences across firms. Broker fixed effects absorb persistent broker-level style, optimism, and coverage-universe differences.

Table 6. Fixed-effects robustness tests

This table reports robustness tests using alternative fixed-effects specifications. Panel A reports the H1 recommendation-level effect based on Eq. (1). Panel B reports the H2 recommendation-action effect based on Eq. (2). The dependent variable is the equal-weighted (EW) market-adjusted forward return. Report-month fixed effects absorb common time shocks at the monthly frequency. Stock fixed effects compare recommendation signals within the same stock over time. Broker fixed effects absorb persistent broker-level differences in rating style, optimism, and coverage universe. Each entry is reported in percentage points, with the t-statistic in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. H1: Score1 minus Score3

Fixed effect	1d	5d	21d	63d
Report-month FE	0.26*** (10.82)	0.53*** (10.26)	0.53*** (5.26)	1.80*** (10.87)
Stock FE	0.28*** (11.32)	0.69*** (12.58)	1.09*** (9.89)	3.00*** (16.35)
Broker FE	0.31*** (12.92)	0.57*** (10.88)	0.36*** (3.38)	1.07*** (5.96)

Panel B. H2: Upgrade minus Downgrade

Fixed effect	1d	5d	21d	63d
Report-month FE	0.52*** (14.58)	1.17*** (14.71)	1.72*** (11.69)	3.04*** (11.99)
Stock FE	0.53*** (14.89)	1.16*** (14.46)	1.79*** (11.90)	2.80*** (10.83)
Broker FE	0.55*** (15.46)	1.23*** (15.28)	1.90*** (12.49)	3.17*** (11.97)

The recommendation-level effect remains positive under all fixed-effect choices. Under stock fixed effects, the Score1-minus-Score3 effect is 0.277 percentage points after one trading day, 0.685 after five trading days, 1.091 after 21 trading days, and 2.996 after 63 trading days. The broker fixed-effect estimates are also positive at every horizon.

The recommendation-action effect is exceptionally stable. Under report-month fixed effects, the upgrade-minus-downgrade effect is 0.521, 1.168, 1.721, and 3.042 percentage points over the 1-, 5-, 21-, and 63-day horizons. Under stock fixed effects, the estimates are 0.534, 1.159, 1.789, and 2.803 percentage points. Under broker fixed effects, they are 0.554, 1.229, 1.898, and 3.170 percentage points. These estimates closely match the baseline regression results.

The stability across fixed-effect specifications is important because analyst recommendations may be correlated with persistent firm characteristics and broker-specific behaviour. Stock fixed effects are particularly demanding because they compare recommendation signals within the same stock over time. Broker fixed effects address the concern that some brokers may be systematically more optimistic, more conservative, or more informative than others. The fact that the upgrade-minus-downgrade effect remains similar under these specifications suggests that the market-response pattern is not driven by persistent differences across stocks or brokers.

5.3 Clustered standard-error robustness

Table 7 evaluates inference under alternative standard-error assumptions. Panel A reports the level effect, and Panel B reports the action effect. The action effect remains highly statistically significant under all clustering choices. Even under report-month clustering, which is the most conservative inference choice in the table, the upgrade-minus-downgrade t-statistics are 11.20, 10.10, 8.27, and 8.10 across the 1-, 5-, 21-, and 63-day horizons.

Table 7. Clustered standard-error robustness

This table reports robustness of statistical inference under alternative standard-error assumptions. Panel A reports the H1 recommendation-level effect based on Eq. (1). Panel B reports the H2 recommendation-action effect based on Eq. (2). The HC1 row reports heteroskedasticity-consistent standard errors. The remaining rows cluster standard errors by stock, report date, or report month. These clustering choices allow residual correlation within firms and within common event-time groups. Each entry is reported in percentage points, with the t-statistic in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. H1: Score1 minus Score3

Standard error	1d	5d	21d	63d
Heteroskedasticity-consistent (HC1)	0.26*** (11.02)	0.52*** (10.07)	0.46*** (4.48)	2.09*** (12.25)
Stock cluster	0.26*** (10.43)	0.52*** (9.31)	0.46*** (3.41)	2.09*** (9.63)
Report-date cluster	0.26*** (8.12)	0.52*** (7.36)	0.46*** (2.89)	2.09*** (8.46)
Report-month cluster	0.26*** (7.20)	0.52*** (6.05)	0.46 (1.59)	2.09*** (4.24)

Panel B. H2: Upgrade minus Downgrade

Standard error	1d	5d	21d	63d
Heteroskedasticity-consistent (HC1)	0.55*** (15.29)	1.22*** (15.27)	1.90*** (12.57)	3.25*** (12.45)
Stock cluster	0.55*** (14.69)	1.22*** (14.57)	1.90*** (11.97)	3.25*** (10.75)
Report-date cluster	0.55*** (13.84)	1.22*** (13.99)	1.90*** (11.15)	3.25*** (10.65)
Report-month cluster	0.55*** (11.20)	1.22*** (10.10)	1.90*** (8.27)	3.25*** (8.10)

The level effect is also robust at most horizons, although it is weaker than the action effect. Under report-month clustering, the Score1-minus-Score3 t-statistic is 7.20 at the 1-day horizon, 6.05 at the 5-day horizon, 1.59 at the 21-day horizon, and 4.24 at the 63-day horizon. This pattern reinforces the main interpretation: recommendation levels are informative, but recommendation actions are the central and most stable empirical result.

The clustered-inference results also reduce concern that the size of the event-level sample mechanically drives the large t-statistics. Analyst-report events may be correlated within stocks, within report dates, or within months, especially when common information shocks affect many firms at the same time. The action effect remains highly significant under all three clustering choices, including report-month clustering. This robustness supports the conclusion that the upgrade-minus-downgrade effect is not merely a product of conventional heteroskedasticity-consistent standard errors.

5.4 Forecast-fundamental confirmation of recommendation actions

The preceding results show that recommendation actions are followed by differential market responses and that the upgrade-minus-downgrade effect is robust to controls, fixed effects, and alternative clustered standard errors. We next provide additional evidence on why recommendation actions are informative. If upgrades and downgrades summarise meaningful changes in analyst information, their market relevance should be stronger when the headline action is confirmed by revisions in the forecast fundamentals contained inside the analyst report. Conversely, if recommendation actions are only coarse rating labels, the internal forecast-table revisions should add little interpretive value.

Table 8 reports these forecast-confirmation tests. The central result is the confirmed action spread, which compares upgrades with favourable forecast-fundamental revisions to downgrades with unfavourable forecast-fundamental revisions. The spread is 0.763 percentage points after one trading day, 1.554 percentage points after five trading days, 2.155 percentage points after 21 trading days, and 3.708 percentage points after 63 trading days. The corresponding t-statistics are 12.899, 11.654, 8.497, and

8.644. These magnitudes are larger than the baseline upgrade-minus-downgrade spreads reported earlier, which is consistent with the interpretation that recommendation actions are especially informative when they are supported by changes in underlying forecast fundamentals.

The Maintain results are also informative. Researchers often treat Maintain recommendations as neutral because the headline recommendation action is unchanged. However, Table 8 shows that Maintain reports contain hidden information when the forecast table changes. Maintain reports with favourable forecast-fundamental revisions outperform Maintain reports with unfavourable forecast-fundamental revisions by 0.153, 0.413, 0.624, and 1.104 percentage points over the 1-, 5-, 21-, and 63-trading-day horizons, respectively. All four estimates are highly statistically significant. This evidence indicates that unchanged headline recommendations should not be interpreted as information-free communication events. Even when the recommendation action is Maintain, the forecast table may reveal favourable or unfavourable changes in the analyst's view.

The remaining rows provide additional support for this interpretation. The unknown-action value-revision spread is positive and statistically significant across all horizons, suggesting that forecast-fundamental revisions contain information even when the recommendation-action classification is not observed. The upgrade confirmation effect is positive at all horizons, although its statistical strength is concentrated at the shorter horizons. The downgrade contradiction effect is also positive, indicating that favourable forecast-fundamental revisions can partly offset the negative information typically associated with downgrades.

Overall, the forecast-confirmation evidence strengthens the main conclusion of the paper. Recommendation actions are not merely coarse headline labels; they summarise economically meaningful changes in analyst information. At the same time, the evidence also shows that the headline action is only one part of the analyst report. Forecast-fundamental revisions provide an internal validation mechanism and reveal additional information, especially within Maintain reports. This reinforces the central distinction between recommendation levels and recommendation actions while showing that analyst communication is multidimensional and that richer report content can refine the market relevance of recommendation actions.

Table 8

Forecast-fundamental confirmation of recommendation actions This table reports additional tests that combine headline recommendation actions with forecast-fundamental revisions from analyst report forecast tables. The table examines whether forecast-fundamental revisions strengthen upgrade and downgrade signals and whether Maintain reports contain hidden positive or negative information. The confirmed action spread compares upgrades with favourable forecast-fundamental revisions to downgrades with unfavourable forecast-fundamental revisions. Forward returns are measured over 1, 5, 21, and 63 trading days after the analyst report becomes tradable information. Returns are equal-weighted (EW) market-adjusted returns. Each entry is reported in percentage points, with the t-statistic in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Effect	1d	5d	21d	63d
Downgrade contradiction effect	0.107* (1.745)	0.240* (1.896)	0.440* (1.828)	1.095** (2.541)
Confirmed action spread	0.763*** (12.899)	1.554*** (11.654)	2.155*** (8.497)	3.708*** (8.644)
Hidden signal within Maintain reports	0.153*** (11.924)	0.413*** (15.576)	0.624*** (12.455)	1.104*** (11.776)
Unknown action value-revision spread	0.132*** (6.411)	0.327*** (6.916)	0.592*** (5.989)	1.315*** (8.318)
Upgrade confirmation effect	0.274*** (4.195)	0.384** (2.484)	0.386 (1.349)	0.489 (1.007)

6. Discussion: expert financial communication and information frictions

Our evidence speaks to a broader question about how expert financial communication enters market prices. Sell-side analyst reports are not only investment opinions; they are institutional communication events through which expert assessments, forecast revisions, and valuation judgments are transmitted to market participants. Our results highlight three implications for research on financial communication and information frictions.

First, the distinction between communication states and communication changes is empirically important. Recommendation levels capture the analyst's current rating state, while recommendation actions capture changes in communicated expert opinion. Market participants may already understand that an analyst is favourable toward a firm, so the static level may contain limited incremental news. A new upgrade or downgrade, by contrast, communicates a change in the analyst's assessment. This distinction helps explain why recommendation actions provide a more stable measure of market-relevant expert communication than recommendation levels.

Second, expert communication matters unevenly across the market. Recommendation effects are stronger among smaller firms and firms with lower prior analyst coverage. This pattern suggests that analyst reports are more informative where public information is thinner and information-processing frictions are more severe. In this sense, analyst communication does not have a uniform market effect. Its relevance depends partly on the surrounding information environment and on how much prior expert attention the firm has already received.

Third, analyst communication is multidimensional. Headline recommendation actions are important, but they are not the only source of information in analyst reports. Forecast-fundamental revisions inside the report provide additional evidence on whether the headline action is supported by changes in the underlying forecast information. The Maintain results are especially informative: an unchanged headline recommendation can still communicate favourable or unfavourable information when the forecast table changes. This finding cautions researchers against treating unchanged recommendations as neutral or information-free events.

These results suggest that future research on expert financial communication can benefit from studying headline signals together with the underlying information embedded in the same communication event. Observable labels such as Buy, Hold, Sell, Upgrade, Maintain, and Downgrade are useful, but their meaning depends on context, prior information, and accompanying report content. The broader lesson is that expert communication should be analysed not only by what label it assigns, but also by how that label changes and what underlying information supports it.

Several limitations should be considered when interpreting the results. First, the empirical design is observational and identifies predictive associations between analyst recommendation actions and subsequent returns rather than causal effects of analyst communication on prices. Although the results are robust to market adjustment, controls, fixed effects, and alternative clustering schemes, unobserved time-varying firm or information characteristics may still contribute to the documented return patterns. Second, recommendation actions are based on vendor-defined classifications, and our information-friction tests use firm size and prior analyst coverage as transparent but imperfect proxies for the underlying information environment. Third, the evidence is drawn from China's equity market and from analyst reports covered by iFinD, so the magnitude and persistence of the effects may not generalise directly to other institutional settings or data providers. Future research could use alternative identification strategies, richer measures of information frictions, and cross-market evidence to assess the generalisability of these findings and the mechanisms underlying them.

7. Conclusion

This paper examines how expert financial communication is incorporated into prices in China's equity market. Using 504,600 analyst-report events from July 2009 to March 2026, we distinguish static recommendation levels from vendor-defined recommendation actions. The evidence shows that recommendation actions provide a clearer and more stable signal of subsequent market response than recommendation levels. Upgrades precede stronger returns than maintains, while downgrades precede weaker returns. The upgrade-minus-downgrade effect remains economically meaningful after market adjustment, regression controls, alternative fixed effects, and clustered-inference tests.

The results also show that the market relevance of analyst communication depends on the information environment. Recommendation effects are stronger among smaller firms and firms with lower prior analyst coverage, consistent with the view that expert communication matters more when public information is thinner and information-processing frictions are greater. Forecast-fundamental revisions inside analyst reports further validate the headline action signal and reveal hidden information within Maintain reports.

Overall, our evidence shows that analyst recommendation actions are not merely rating labels. They are expert communication events that transmit market-relevant information, especially when reinforced by underlying forecast-fundamental revisions and when issued for firms with greater information frictions. These findings contribute to a broader understanding of how expert financial communication, information asymmetry, and investor response interact in an institutionally distinctive equity market.

Declarations

Author Contribution

Z.W. contributed to the conceptualisation, research design, data analysis, interpretation of results, manuscript drafting and revision. Y.C. contributed to the conceptualisation, research design, data analysis, interpretation of results, manuscript drafting and revision. Both authors reviewed and approved the final manuscript.

Data Availability

The underlying analyst and financial-market data used in this study were obtained from the iFinD financial data service provided by Hithink RoyalFlush Information Network Co., Ltd. These source data were accessed under licence and are subject to the data provider's applicable access and redistribution restrictions; the original proprietary source files therefore cannot be made publicly available. For confidential editorial and peer-review verification, anonymised replication materials, including analysis-ready datasets, MATLAB code, variable and data-construction documentation, and reference outputs used to reproduce the reported tables and figures, are available through an anonymised OSF view-only repository: https://osf.io/wu5zv/overview?view_only=ab9cbb8518dc4287b80ef05ed46839ce. Access to the underlying proprietary source data is available through iFinD subject to the provider's applicable licensing and access conditions.

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Figures

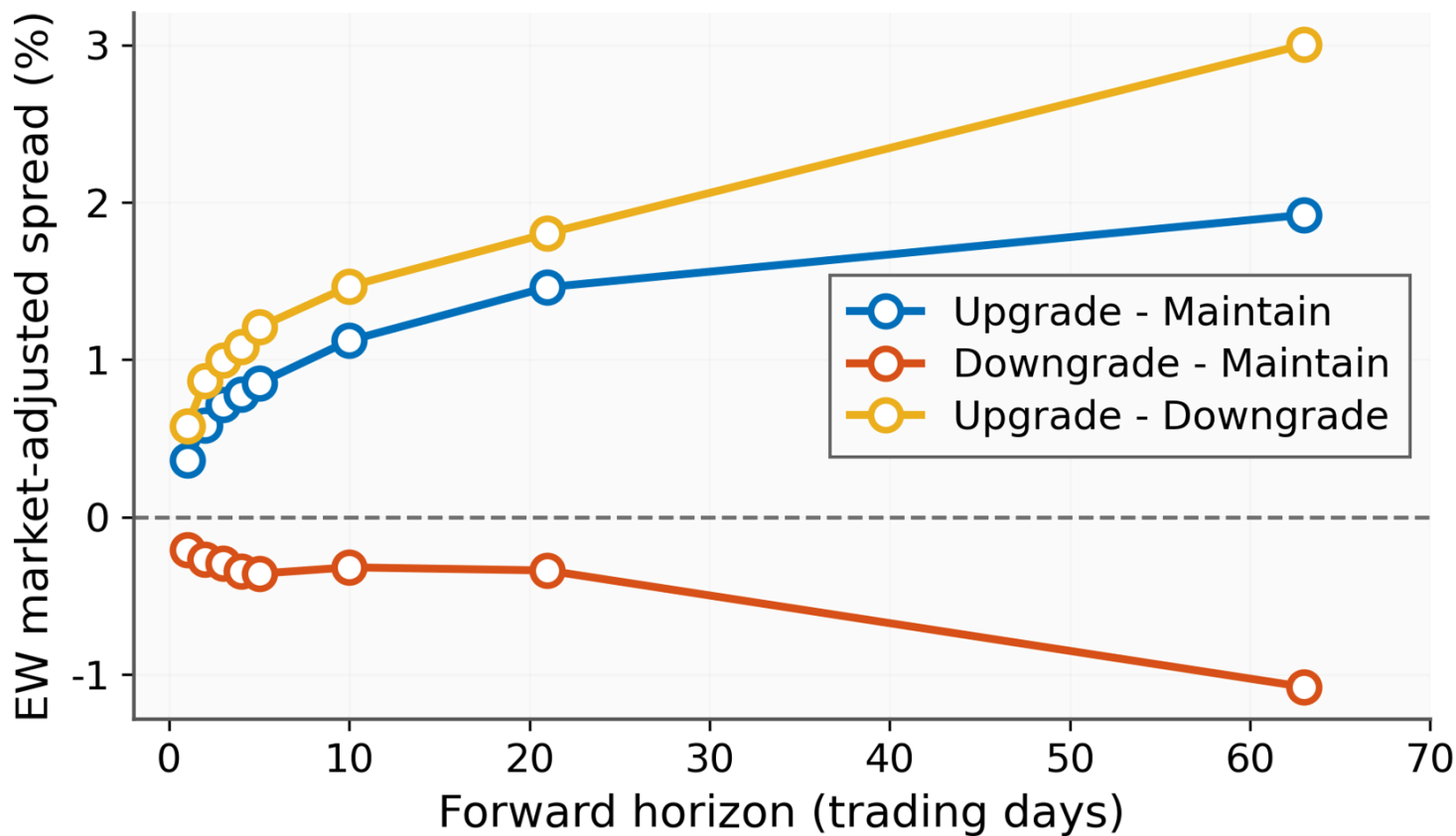


Figure 1

Market-adjusted analyst-action spread

This figure plots equal-weighted (EW) market-adjusted forward return spreads for analyst recommendation actions. For each event and horizon, the EW market return over the same event window is subtracted from the stock's forward return. The figure highlights the upgrade-minus-downgrade spread over 1-, 5-, 21-, and 63-trading-day horizons, corresponding to the action evidence in Table 3.

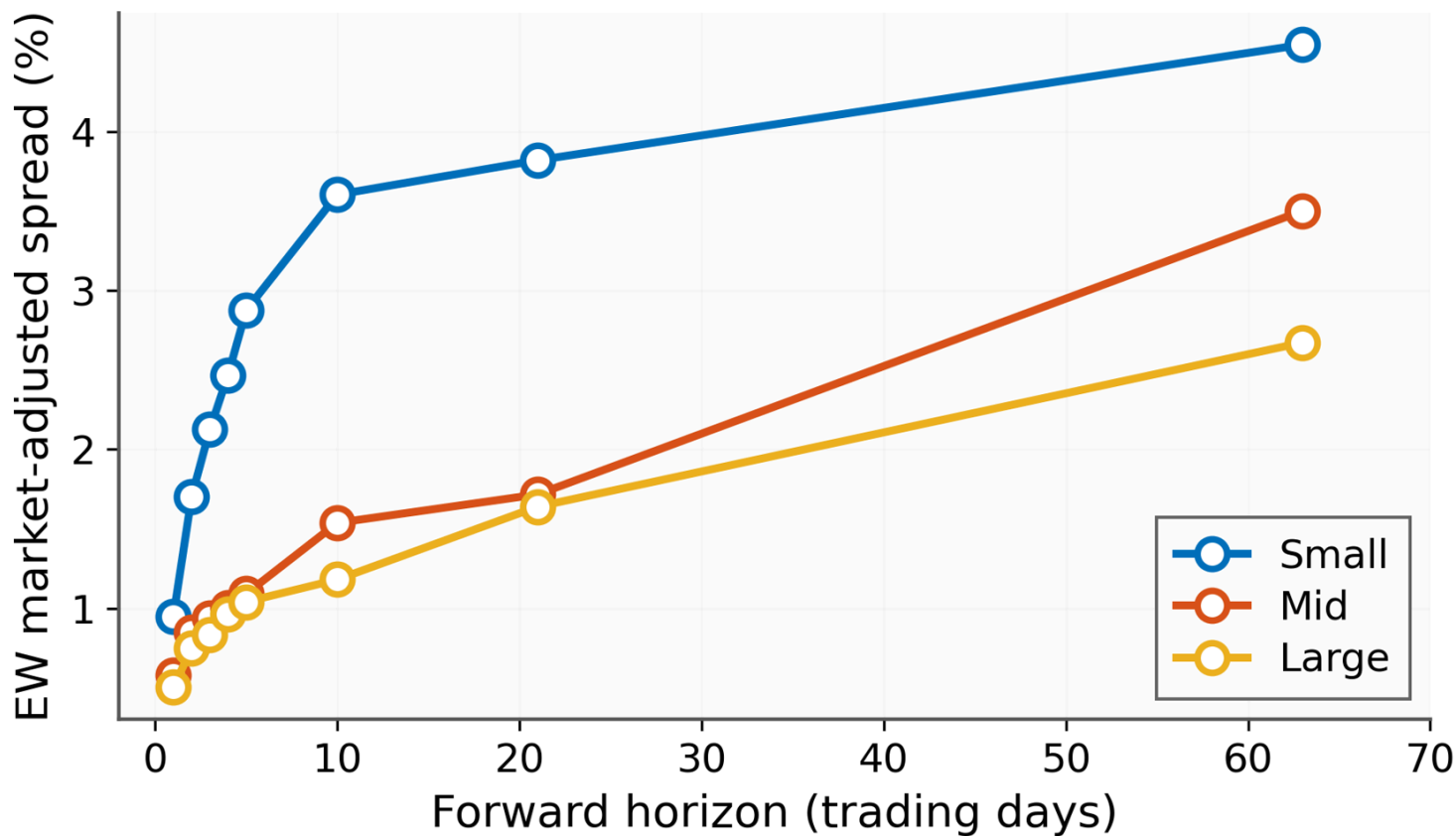


Figure 2

Size heterogeneity in analyst-action effects

This figure plots the upgrade-minus-downgrade effect across firm-size buckets. The comparison illustrates whether analyst-action return predictability is stronger among smaller stocks than among larger stocks. The pattern corresponds to the size-based information-asymmetry tests reported in Table 4.

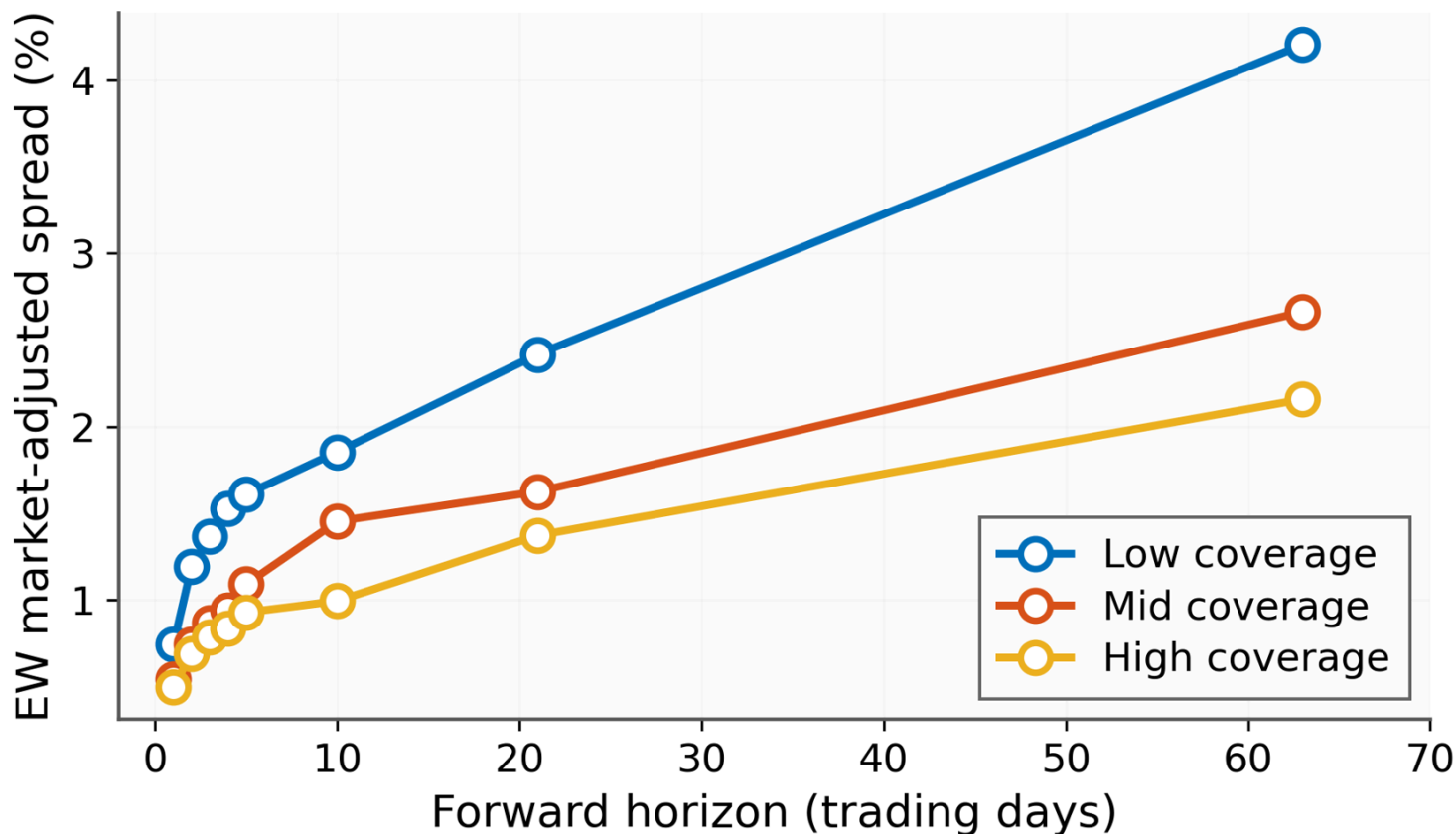


Figure 3
Prior-coverage heterogeneity in analyst-action effects

This figure plots the upgrade-minus-downgrade effect across prior analyst coverage buckets. Prior coverage is measured using the number of analyst reports issued for the same stock over the previous 365 days. The comparison illustrates whether analyst-action return predictability is stronger among stocks with lower prior analyst coverage, corresponding to the coverage-based information-asymmetry tests reported in Table 4.

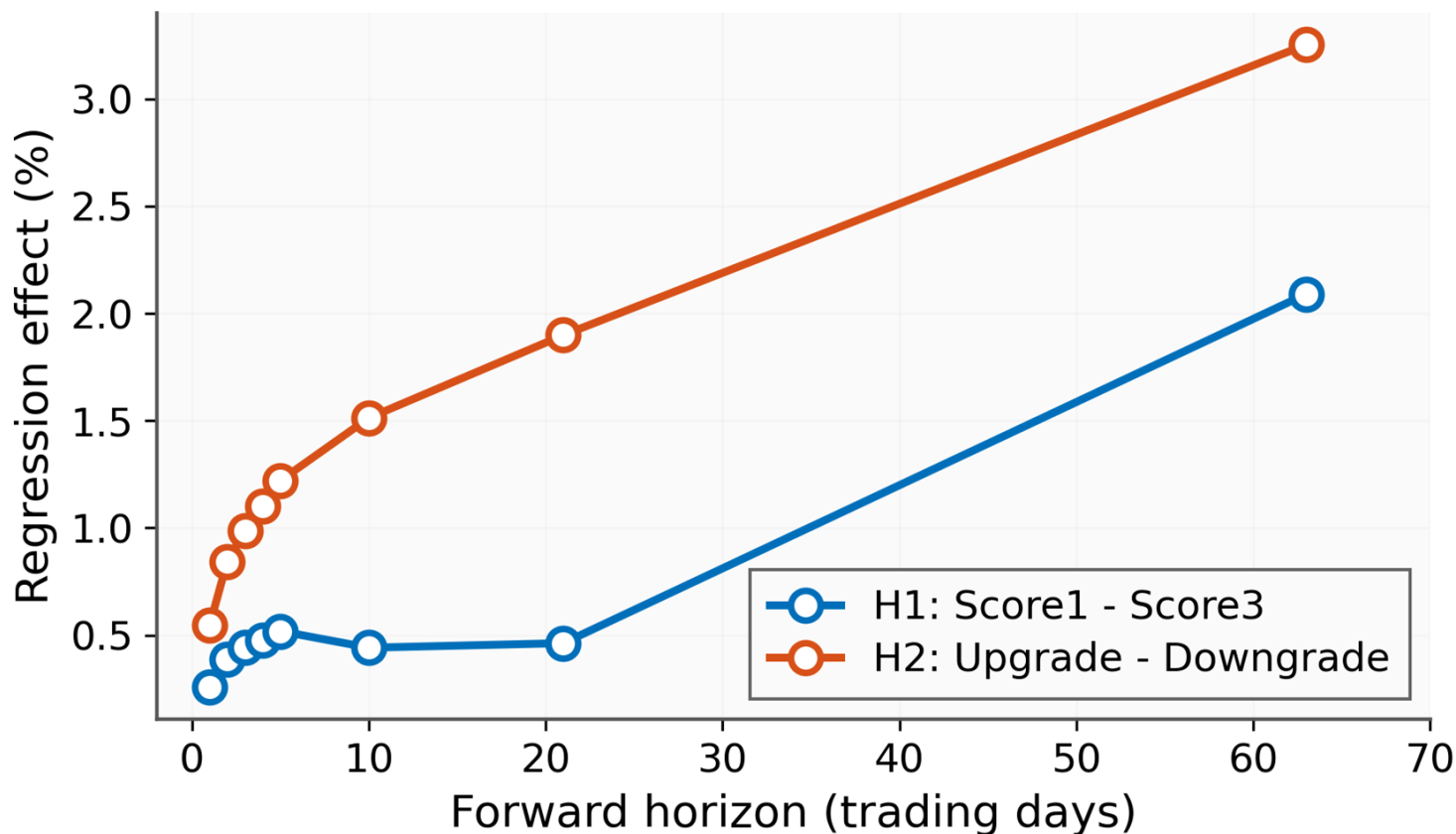


Figure 4

Baseline regression effects

This figure summarises the main regression effects for recommendation levels and recommendation actions. The recommendation-level effect is measured as Score1 minus Score3, and the recommendation-action effect is measured as Upgrade minus Downgrade. The dependent variable is the equal-weighted (EW) market-adjusted forward return. The figure corresponds to the main regression estimates reported in Table 5.