On the information structure of analyst research portfolios: The role of bellwether and its information share

by

Rui CHEN[1], Jinjuan REN[2], and Jingying ZHAO[3]

[1] Rui Chen (ruichen@scnu.edu.cn) is from International Business College, South China Normal University.
[2] Jinjuan Ren (jinjuanren@um.edu.mo) is from Faculty of Business Administration, University of Macau.
[3] Jingying Zhao (jyzhao@cityu.edu.mo) is from Faculty of Finance, City University of Macau.
Corresponding concerning this article should be addressed to Jinjuan Ren, Faculty of Business Administration, University of Macau, Avenida da Universidade, Taipa, Macau, China.

On the information structure of analyst research portfolios: The role of bellwether and its information share

Abstract

We examine analyst coverage decisions through the lens of the information structure of research portfolios. Based on the partial correlation of fundamentals (Hameed et al. 2015) among firms, we identify a bellwether firm that serves as the information hub in an analyst's research portfolio. We then quantify the information share disseminated from this bellwether to the entire portfolio, which captures the economies of scale in analyst's information production and usage. We find robust evidence that analysts who construct portfolios with higher information share from bellwethers have superior forecasting performance.

Keywords: Analyst research portfolio; Information structure; Partial correlation; Bellwether; Information share; Analyst forecast

***JEL* classification:** G14, G24, M41

1. Introduction

Each sell-side financial analyst selectively covers a subset of financial assets (Kini et al. 2009; Brown et al. 2015). Analysts' research portfolios are primarily shaped by exogenous forces such as client demand (Harford et al. 2019). Our study delves into the endogenous determinant of analysts' coverage decisions: the *similarity* between a new firm and those already covered by the analyst. The benefits from similarity arise from the economies of scale in information production. While traditional views on firm similarity emphasize industry classifications (Chan and Hameed 2006), recent studies expand this concept to include product market competitors (Hsu et al. 2023), firms adopting similar technology (Martens and Sextroh 2021), and firms in close geographic proximity (O'Brien and Tan 2015). Supplier-customer pairs, though not similar, are related, and supply-chain analysts benefit from complementary information (Guan, Wong, and Zhang 2015; Luo and Nagarajan 2015).

The information structure of an analyst's portfolio is multifaceted and jointly shaped by various economic linkages. In this paper, we extend the existing literature by moving beyond analyzing specific economic linkages to employ partial correlation (*PCORR*). This empirical and holistic measure quantifies the strength of economic connections among firms within an analyst's portfolio. The *PCORR* methodology, originally introduced by Hameed et al. (2015) to identify the bellwether firm within an industry, is adapted to pinpoint the bellwether firm in an analyst's research portfolio and quantify the information share of the bellwether.

The methodology is detailed as follows. 1) We quantify pairwise *PCORR* between firms within the research portfolio based on firm return on assets (ROA). *PCORR* captures the proportion of variations in other firms that are explained by the focal firm, reflecting the extent of information flow from the focal firm to others. 2) We calculate the average *PCORR* for each focal firm relative to other firms in the portfolio. The firm with the highest average *PCORR* is designated as the bellwether, serving as the information hub within the analyst's portfolio, as it explains other firms more than it is explained by them. The bellwether's *PCORR* quantifies the average strength of economic ties between the bellwether and other firms. 3) We aggregate *PCORR* flows from the bellwether to the remaining firms, scaling this sum by the total pairwise *PCORR* across the entire research portfolio. This ratio quantifies the information share (*IS*) contributed solely by the bellwether to the overall information flow.

We use the portfolio-level *IS* to assess the economies of scale in information production within an analyst's research portfolio. As *IS* increases, an analyst focusing exclusively on the bellwether essentially uncovers a higher proportion of information related to the entire portfolio, primarily due to the information spillover from the bellwether to other firms. We hypothesize that an analyst capable of constructing an informationally efficient portfolio is more skillful.

Our empirical analyses confirm the hypothesis that analysts with higher *IS* demonstrate superior forecasting performance and career outcomes. Specifically, other things being equal, analysts with higher *IS* achieve greater accuracy in earnings forecasts and issue more profitable recommendations. We provide further firm-level evidence that both bellwether and non-bellwether firms benefit from higher *IS* within the research portfolio. Furthermore, non-bellwether firms with stronger economic linkages to the bellwether experience greater benefits. Our findings on forecasting performance remain robust after controlling for year-fixed effects, as well as analyst fixed effects, brokerage house fixed effects, and bellwether fixed effects. Analysts with higher *IS* are also more likely to attain star status, transition to higher-status brokerage houses, and maintain job stability. Our results regarding career outcomes are consistent after accounting for other factors that influence analyst skill and research quality. Overall, the evidence strongly supports *IS* as an effective measure of an analyst's skill.

In additional validation tests, we confirmed the relevance of *PCORR* as a comprehensive measure of the strength of economic ties. Firms with known economic links to the bellwether exhibit higher *PCORR* values. These results hold across various peer relationships, including SIC2, SIC3, Fama-French 48, text-based industry classification (TNIC), and the potential supply-chain relationship measured by vertical textual network industry relatedness classification (VTNIC), and geographic proximity.

The bellwether firms identified by the *PCORR* approach appear to be reliable information hubs within research portfolios. We find that the majority of bellwether firms come from the largest SIC3 industry in the analyst's research portfolio and have the largest market capitalization within their respective industries. Consistent with conventional wisdom, industry peers are the most common type of economic tie between bellwethers and other firms. Our results show that 37.7% of other firms share an SIC3 classification with the bellwether. Additionally, 24.7% of other firms have a potential supply-chain linkage with the bellwether measured by VTNIC, 21.1% have a geographic linkage, and 21.9% have a technology linkage. Interestingly, we do find that 19.7% of firms have no identifiable linkage with the bellwether.

We find further compelling evidence that the identified bellwether is indeed the information hub within the research portfolio. Analysts are more likely to revise their forecasts for other firms in response to significant earnings news from the bellwether, particularly when the portfolio *IS* is high, and/or their *PCORR* with the bellwether is high. In contrast, we do not observe analysts revising the bellwether's earnings forecast in response to other firms' earnings news.

In a nutshell, this study presents three main findings about the information structure of an analyst's research portfolio. 1) *PCORR* effectively captures both traditional and subtle, latent economic linkages among portfolio firms. 2) *PCORR*-based bellwether successfully identifies the central information hub within the portfolio. 3) Most importantly, *IS* of the bellwether quantifies economies of scale in information production. Our findings show that analysts with higher *IS* are more skillful in that they exhibit superior forecasting performance and achieve better career outcomes.

Our study is related to the broad literature on analysts' coverage decisions. In the survey conducted by Brown et al. (2015), the foremost determinant of coverage decisions is client demand for information about a company. Upon client requests, brokerages hire or assign analysts with relevant industry expertise to cover specific stocks (Bradley, Gokkaya, and Liu 2017). As such, analysts' coverage decisions are largely exogenous. However, as analysts gain experience and build their reputations, they acquire more control over their portfolios. Our work focuses on the endogenous factors influencing analysts' coverage decisions.

Our study adds to the literature on the determinates of analysts' effort allocation. Prior research shows that analysts face multi-tasking costs (Hirshleifer et al. 2019; Ru, Zheng, and Zou 2024) and strategically prioritize their efforts on firms critical for career advancement (Harford et al. 2019) or with greater resources for information acquisition (Dessaint, Foucault, and Frésard 2024). In this paper, we explore analysts' coverage decisions through the lens of information structure. While the selection of a bellwether firm within the research portfolio is exogenously determined, we propose that analysts have significant discretion in selecting other firms to cover. By focusing strategically on firms with stronger economic ties to the bellwether, analysts can exploit information spillovers and achieve economies of scale in information production. Our empirical findings also confirm the career-driven behavior noted by Harford et al. (2019), showing that the predictive power of *IS* is stronger when portfolio accuracy is weighted by the relative importance of the firms covered.

Our study reflects the organizational structure of a typical brokerage house. While macroeconomic and industry outlooks from brokerage strategists (Bradshaw 2012; Kadan et al. 2012) and insights from hedge funds and mutual funds (Brown et al. 2015) collectively drive the exogenous initiation of coverage into a particular industry, the brokerage hires analysts with hands-on industry expertise (Bradley, Gokkaya, and Liu 2017) or assign existing analysts capable of acquiring industry knowledge. Directors of the research department add value through their prior industry experience (Bradley, Gokkaya, and Liu 2019). Despite these exogenous forces playing a significant role in shaping an analyst's research portfolio, particularly in determining the bellwether, we argue that analysts still have room to optimize their coverage by strategically selecting firms with visible or invisible economic ties to the bellwether.

Our study builds on recent literature highlighting the benefits of covering firms with economic linkages, including industry peers (Chan and Hameed 2006; Chhaochharia et al. 2023), product market competitors (Hsu et al. 2023), supply chain connections (Guan, Wong, and Zhang 2015), geographic neighbors (O'Brien and Tan 2015), and technological ties (Martens and Sextroh 2021). We propose *PCORR* as a holistic measure of economic ties, aligning with traditional indicators while offering incremental insights into less visible linkages. Furthermore, *PCORR* is empirically derived, relying solely on accessible and widely available historical financial data.

Finally, our study is related to the pricing of information in the information market. Veldkamp (2006) models investor decisions in an information market with costly information, highlighting that investors prefer acquiring information with complementary value to predict other assets. On the supply side, brokerage houses monetize research reports through lump-sum soft dollar payments, with the pricing of these information bundles being both intricate and dynamic. The implementation of MiFID II in 2018, which unbundled securities commissions in European markets (Guo and Mota 2021), has further reshaped the landscape. From an analyst's perspective, if the payoff from information production is opaque, their incentives are dominated by commission generation and institutional support, which helps her to gain star status or even transition to the buy-side (Groysberg, Healy, and Maber 2011). We provide empirical evidence to understand analysts' information production choices from the cost side. Facing exogenous drivers and constraints in efforts, a financial analyst may extend coverage to firms closely tied to the portfolio's information hub, thus achieving economies of scale in information production about the bellwether firm.

The remainder of this study is organized as follows. Section 2 discusses the data and methodologies used to construct *PCORR*, identify bellwethers, and quantify the *IS* of bellwethers within research portfolios. Section 3 presents the baseline results, analyzing the impact of *IS* on analysts' forecasting performance and career outcomes. Section 4 conducts validation tests, demonstrating that *PCORR* is a holistic measure of economic ties and that the identified bellwether firm functions as the information hub in the research portfolio. Section 5 presents the results of additional robustness tests. Section 6 concludes the paper.

2. Data and methodologies

2.1. Data and sample

The primary dataset for this study is the analyst forecasts and recommendations from the Institutional Brokers' Estimate System (IBES), covering the period from 1994 to 2023. A firm is considered under an analyst's coverage if any type of earnings forecast (quarterly, semi-annual, current-year annual, etc.) is issued within a year. We require an analyst to cover at least three firms per year. Analyst performance is measured using the last current-year annual forecast (FY1) issued at least one month before the fiscal year-end.

Analyst forecast data are merged with stock return data from CRSP. Following standard conventions, we include all common stocks (share code 10 or 11) and exclude stocks with an average daily stock price of less than $1 in December of the previous year. Financial statement data are from COMPUSTAT, which also provides customer-supplier segment data for identifying supply-chain relationships and zip code information for pinpointing geographically close firms. Additionally, we leverage Google patent data from Kogan et al. (2017) to identify technological linkages among firms. The patent data are updated through the end of 2022.

We collect text-based industry classification (TNIC) and vertical textual network industry relatedness classification (VTNIC) data from the Hoberg-Phillips Data Library.[1] TNIC data are based on pairwise similarity scores derived from textual analysis of product descriptions in firms' 10-K disclosures (Hoberg and Phillips 2010, 2016). VTNIC data, also at the firm-pair level, capture vertical supply chain relationships by comparing product descriptions in firms' 10-K filings with those used

[1] http://hobergphillips.tuck.dartmouth.edu/

by the U.S. Bureau of Economic Analysis (BEA) in Benchmark Input-Output tables (Phillips et al. 2020). To ensure comparability with traditional classifications, we align TNIC peers to the granularity of SIC three-digit classifications and use VTNIC data at a 10% granularity level. Both datasets are updated annually through 2021.

Finally, we obtain institutional ownership data from Thomson Reuters' institutional holdings (13F) database and manually collect star analyst data through 2017 from All-American Research Team analysts in *Institutional Investor*'s magazine. Table 1 shows a detailed description of the variables used in this study.

[Insert Table 1 here.]

2.2. PCORR matrix

The exploration into the information structure of an analyst's research portfolio begins with the information flow among firms. Similar to the partial correlation (*PCORR*) approach proposed by Hameed et al. (2015) to identify the bellwether firm in an industry, we calculate the pairwise *PCORR* among firms within an analyst's research portfolio based on return on assets (ROA) as a measure of changes in firm-specific fundamentals.

In an analyst's research portfolio, for each stock *k*, we estimate a market model using a rolling window of 20 quarterly ROAs from years *t*-5 to *t*-1 as

$$ROA_{kq} = \alpha_k + \beta_k ROA_{Mq} + \varepsilon_{kq}, \tag{1}$$

where ROA_{kq} is the ROA of firm *k* in quarter *q* and ROA_{Mq} is the value-weighted market average ROA in the same quarter, with the ROA of the focal firm *i* excluded. We label model (1)'s explanatory power as $R^2_{k,excl,i}$. Next, we include the ROA of firm i as an additional explanatory variable as

$$ROA_{kq} = \alpha_k + \beta_k ROA_{Mq} + \gamma_k ROA_{iq} + \varepsilon_{kq}, \tag{2}$$

where firm i's ROA explains firm k's ROA together with the market factor. We label model (2)'s explanatory power as $R^2_{k,incl,i}$. We then take the scaled difference between $R^2_{k,incl,i}$ and $R^2_{k,excl,i}$ as

$$PCORR_{ik} = (R^2_{k,incl,i} - R^2_{k,excl,i}) / (1 - R^2_{k,excl,i}). \tag{3}$$

Variable $PCORR_{ik}$ measures the partial correlation between firms i and k, capturing the proportion of firm k's variance unexplained by the market factor that is explained by firm i. A higher $PCORR_{ik}$ indicates a stronger economic tie between the two firms. The pairwise *PCORR* matrix quantifies the information flow within the portfolio and is symmetric, as information flows between firms i and k are mutual.

[Insert Figure 1 here]

To illustrate our methodology, we use the example of a research portfolio managed by a star analyst covering five stocks in 2016. Figure 1 presents the pairwise *PCORR* matrix for this analyst, with rows representing the focal firm i and columns representing other firms k. For instance, the intersection of International Business Machines Corporation (IBM) in the row and Dell Technologies Inc (DELL) in the column indicates the incremental explanatory power of IBM's fundamentals for DELL. Specifically, IBM's fundamentals explain 81.2% of the variations in DELL not captured by the market model excluding IBM. In comparison, IBM only provides 5% of incremental explanatory power for Hp Inc. (HP). This indicates a significantly stronger economic linkage between IBM and DELL than between IBM and HP, demonstrating heterogeneity in explanatory power even within the same industry.

2.3. Identifying bellwether within an analyst's research portfolio

To identify the bellwether within the portfolio, we calculate $PCORR_{ik}$ for each focal firm i by averaging across all other firms k ($k \neq i$), denoted as $PCORR_i$. A higher value of $PCORR_i$ indicates stronger economic ties between firm i and the rest of the portfolio. The firm with the highest $PCORR_i$ is designated as the portfolio bellwether, and its partial correlation with other firms k is denoted as $PCORR_{Bk}$. By definition, the bellwether's fundamentals drive those of other firms in the portfolio, with its information spilling over to support the valuation of the remaining firms.

Referring back to Figure 1, the last column in each row reports the average *PCORR* between firm i and other firms in the portfolio. We intentionally rank stocks by $PCORR_i$ in descending order. In this example, IBM has the highest average *PCORR* of 0.276, designating it as the portfolio's bellwether.

In our sample, 62% of bellwethers are part of the largest SIC3 industry in an analyst's portfolio, and among these, 76% are the largest firms by market capitalization within their respective industries. Within the first three years of an analyst's inclusion in IBES, 70% of bellwethers are associated with the largest SIC3 industry in their portfolio. We also find that portfolio bellwethers tend to be firms that are relatively more important to analysts' careers (Harford et al. 2019), as they exhibit higher market capitalization and trading volumes in the Internet Appendix Table IA1.

We posit that analysts allocate the majority of their efforts to the bellwether firm within their research portfolios, as the remaining firms benefit from information spillovers originating from the bellwether. This focus enhances informational complementarity across other firms within the portfolio, thereby generating significant economies of scale in information production. Validation results, presented in Section 4.2, confirm that the bellwether serves as the information hub within the portfolio.

2.4. *Information share of bellwether*

In the analyst research portfolio, information flows within the pairwise *PCORR* matrix in that 1) the bellwether contributes explanatory power to others, 2) the bellwether is explained by others, and 3) other firms mutually explain each other. We proceed to calculate the information share (*IS*) spilled over from the bellwether firm to the entire portfolio as

$$IS = \frac{PCORR_B}{\sum_i PCORR_i}. \tag{4}$$

The numerator, $PCORR_B$, represents the information spillover from the bellwether firm *B* to the remaining firms (as shown in the last column of the first row in Figure 1). The denominator is the sum of $PCORR_i$ across all focal firms *i* in the portfolio (corresponding to the last column of Figure 1), capturing the total information flow within the entire portfolio. The resulting ratio, *IS*, quantifies the proportion of information contributed by the bellwether to other firms in the portfolio. The bottom row of Figure 1 shows an example of *IS* calculation. As the average $PCORR_B$ between

IBM and other firms in the portfolio is 0.276, while the total sum of $PCORR_i$ across all focal firms is 0.723. This calculation indicates that IBM contributes 38.1% of the total information share within the research portfolio.

Unreported analysis indicates a mechanically negative relationship between *IS* and portfolio size, with smaller portfolios generally exhibiting higher *IS*. To ensure comparability of *IS* across portfolios of different sizes, we demean *IS* by its average within portfolios of the same size. Further analyses are conducted based on the demeaned *IS*. Panel A of Table 2 reports that the mean of the raw *IS* is 0.245, with a median of 0.195. The raw *IS* ranges from 0.003 to 0.979. For the demeaned *IS*, the mean and median are close to zero, with a broader range from -0.576 to 0.818.

[Insert Table 2 here.]

The portfolio-level *IS* captures the economies of scale achieved in information production by the analyst. Given the costs of information production (Veldkamp 2006) and the resource constraints faced by analysts (Harford et al. 2019), strategically allocating research efforts is critical for career success. When analysts allocate resources and efforts to the bellwether firm, portfolios with higher *IS* gain greater advantages from the information spillovers generated by the bellwether, and improve the efficiency of both information production and utilization.

3. Portfolio information share and analyst performance

In this section, we hypothesize that analysts who construct research portfolios with higher *IS* exhibit greater skill and deliver superior forecasting performance. To empirically test this, we assess analyst performance using three distinct measures: earnings forecast accuracy, stock recommendation profitability, and career outcomes.

3.1. Forecast accuracy at portfolio level

The first measure of analyst performance is the relative earnings forecast accuracy (*Accuracy*). We follow Clement (1999) and Harford et al. (2019) to construct

$$Accuracy_{j,k,t} = (-1) \times \frac{AFE_{j,k,t} - MAFE_{k,t}}{MAFE_{k,t}}, \tag{5}$$

where $AFE_{j,k,t}$ represents the absolute difference between the forecasted and actual earnings for analyst j covering firm k in year t. To control for firm-year effects in forecast accuracy, we standardize $AFE_{j,k,t}$ by the mean absolute forecast error (*MAFE*) across all analysts covering firm k in year t. This relative forecast error accounts for contemporaneous peer performance, with higher values of *Accuracy* indicating more precise earnings forecasts. To mitigate the influence of outliers, we winsorize *Accuracy* at the 1st and 99th percentiles.

We then adopt alternative weighting schemes to aggregate firm-level forecast accuracy into a measure of analysts' portfolio-level performance. The baseline approach uses an equally-weighted scheme (*Accuracy_EW*), treating all firms in the portfolio as equally important. As a robustness check, we apply the $PCORR_{Bk}$-weighted scheme (*Accuracy_PCORR*), which assigns higher weights to firm k with stronger economic ties to the portfolio bellwether. By definition, the on-diagonal $PCORR_{BB}$ is undefined as shown in Figure 1. To account for the importance of the bellwether, we arbitrarily assign the highest weight to the bellwether firm by defining $PCORR_{BB}$ to be one. Unreported robustness tests reveal that excluding bellwether firms in calculating *PCORR*-weighted portfolio accuracy does not qualitatively affect our main findings.

We use the panel data of analyst-year observations to examine the impact of *IS* on forecast accuracy at the analyst's aggregated portfolio level. The regression model is

$$Accuracy_{j,t+1} = IS_{j,t} + Psize_{j,t} + Gexp_{j,t} + Bsize_{j,t} + FE + \varepsilon_{j,t+1}, \tag{6}$$

where the dependent variable, $Accuracy_{j,t+1}$, represents the forecast accuracy of all firms in analyst *j*'s portfolio for year *t*+1. The variable of interest is the demeaned portfolio *IS* of analyst *j* in year *t*, lagged by one year to mitigate potential endogeneity concerns. We hypothesize that *IS* predicts superior forecasting performance, leading to a positive coefficient for *IS* in Eq.(6).

To address the potential influence of analyst abilities and broker attributes on performance, we include analyst-portfolio-level control variables: portfolio size (*Psize*), general forecast experience (*Gexp*), and a dummy variable indicating whether the analyst works for one of the top ten brokerage houses based on the number of analysts employed (*Topbroker*) (Jacob, Lys, and Neale 1999; Ivković and Jegadeesh 2004; Ramnath, Rock, and Shane 2008).

Panel A of Table 2 reports summary statistics for portfolio-level variables. *Accuracy_EW* has a mean of -0.019 and a median of 0.115, while *Accuracy_PCORR* shows a mean of -0.017 and a median of 0.129. Regarding control variables, an analyst covers a median of 13 firms in the portfolio and has a mean of 10.48 years of general experience. About 49.3% of analysts work for a top ten brokerage house.

[Insert Table 3 here.]

Table 3 reports the regression results. As predicted, the coefficients for *IS* are positive and statistically significant in all columns. In Columns (1) and (2), the dependent variable is equally-weighted portfolio accuracy. Column (1) includes year fixed effects to account for time-varying patterns in analyst forecasting performance. The coefficient of *IS* is 0.075, statistically significant at a 1% level (*t*-value = 2.64). Economically, a one standard deviation increase in the analyst's portfolio *IS* leads to a 0.91% standard deviation increase in the averaged portfolio forecast accuracy. In Column (2), analyst fixed effects are added to control for unobserved, time-invariant analyst characteristics omitted from Eq.(6). This control reduces the significance level of *IS* to 5%, likely reflecting that the ability to construct an informationally efficient portfolio is a person-specific trait that varies little over time. In Columns (3) and (4), when greater weight is assigned to firms with stronger economic ties to the bellwether in *Accuracy_PCORR*, the positive predictive power of *IS* remains robust and slightly stronger than in *Accuracy_EW*. This result aligns with expectations, bellwether firms attract greater research efforts, and firms more strongly linked to the bellwether benefit from enhanced information spillovers, resulting in more accurate earnings forecasts.

To address the concern in Harford et al. (2019) that analysts strategically allocate more efforts to firms that are important to their clients, we perform additional robustness checks by calculating portfolio accuracy weighted by firm importance, as measured by firm size (*Accuracy_Size*), institutional ownership (*Accuracy_IO*), and trading volume (*Accuracy_TrdVol*). The results, reported in Internet Appendix Table IA2, show that the predictive power of *IS* remains significant, which is even stronger than its effect on equally-weighted portfolio accuracy.

These results provide strong empirical support for using *IS* as a novel measure of analyst skill. In summary, higher *IS* from the bellwether firm within an analyst's research portfolio is associated with more accurate earnings forecasts.

3.2. Forecast accuracy at firm level

We next investigate the forecast accuracy at the analyst-firm level. Given that *IS* reflects an analyst's ability to construct a portfolio that captures economies of scale in information production, we expect higher *IS* to benefit both bellwether and non-bellwether firms within the portfolio, with greater gains for the bellwether as the portfolio's information hub. We test these hypotheses using

$$\begin{aligned} Accuracy_{j,k,t+1} = IS_{j,t} + PCORR_{Bk,t} + \text{Analyst controls}_{j,t} + \text{Firm controls}_{k,t} + \\ \text{Analyst-firm controls}_{j,k,t} + FE + \varepsilon_{j,k,t+1} \end{aligned} . \quad (7)$$

The left-hand-side variable is the analyst-firm level one-year-ahead relative forecast accuracy. On the right-hand-side, the key variable, *IS*, is expected to positively influence the forecast accuracy for all firms in the research portfolio. A distinctive feature of this firm-level regression is the inclusion of *PCORR*, which captures the strength of economic ties between non-bellwether firm *k* and bellwether *B* in analyst *j*'s portfolio in year *t*. We expect a positive coefficient for *PCORR*, indicating that firms with higher *PCORR* with the portfolio bellwether will have more accurate forecasts.

In this firm-level analysis, we control for various analyst and firm characteristics that may influence the relationship between *IS* and forecast accuracy for individual firms. Analyst-firm level characteristics include the analyst's firm-specific forecasting experience (*Fexp*) and the natural logarithm of the time horizon between the analyst's forecast for firm *k* and the firm's fiscal year-end (*Horizon*). Firm-level controls, measured annually, capture factors shaping the information environment and analyst coverage motivations, including the number of analysts covering the firm (*Nanalyst*), the natural logarithm of the firm's market value (*Size*), the book-to-market (*B/M*) ratio, the percentage of institutional ownership (*IO*), the standard deviation of a firm's monthly stock returns (*Volatility*), the natural logarithm of annual trading volume in thousands of shares (*TrdVol*), the research and development (R&D) intensity (*RD_intensity*), the advertising intensity (*AD_intensity*), and a dummy indicator for firms with negative earnings (*Loss*). Continuous variables are winsorized at the 1st and 99th percentiles to address outliers.

Panel B of Table 2 shows the summary statistics. The mean $PCORR_{Bk}$ is 0.214, with a median of 0.134, consistent with Hameed et al. (2015), who used *PCORR_ROA* to capture the partial correlation between the earnings of firms in the same industry. Other variables' values align with prior studies (Huang, Lin, and Zang 2022; Hsu et al. 2023). The mean *Size* is 8.23, the average *B/M* is 45%, the mean *Volatility* is about 0.10, and the mean *TrdVol* is 14.44. The average *RD_intensity* and *AD_intensity* are 0.07 and 0.01, respectively, and about 22% of firms report a loss during the sample period.

[Insert Table 4 here.]

Table 4 reports the results of firm-level regressions. We first examine the sample of bellwether firms. In Column (1), without controlling for analyst fixed effects, the coefficient of *IS* is 0.218 (*t*-value = 2.17), suggesting that across analysts, earnings forecasts for bellwether firms are more accurate when the portfolio has a higher *IS*. This result remains robust in Column (2) with analyst fixed effects included. In Columns (3) to (8), we report the regression results for non-bellwether firms in the analyst's portfolio. In addition to year- and analyst- fixed effects, we alternatively control for brokerage- and bellwether-fixed effects to account for the exogenous factors influencing analyst coverage decisions and unobserved characteristics specific to brokerage houses or bellwether firms. The coefficients of *IS* remain significantly positive across all columns, indicating that economies of scale in information production also enhance the forecast accuracy for non-bellwether firms.

More importantly, the coefficients of *PCORR* range from 0.003 and 0.018 are significantly positive in Columns (5) to (8). In terms of economic magnitudes, a one standard deviation increase in *PCORR* is associated with a 0.07% to 0.40% increase in the relative accuracy of non-bellwether firms. These findings indicate that non-bellwether firms benefit more from economies of scale when they have stronger economic ties to the bellwether firm. Notably, in Column (8), the variation in *IS* and *PCORR* among research portfolios constructed by different analysts around the same bellwether in the same year highlights the role of analyst-specific capabilities, with higher *IS* and *PCORR* consistently leading to more accurate forecasts.

The coefficients for the control variables align with prior research (Jacob, Lys, and Neale 1999; Drake et al. 2020). Analysts with greater firm-specific forecasting experience (*Fexp*) consistently produce more accurate earnings forecasts, while forecasts based on outdated information (*Horizon*) tend to be less precise. Additionally, firms with enriched information environments, characterized by larger market capitalization (*Size*) or broader analyst coverage (*Nanalyst*), tend to exhibit higher forecast accuracy. These findings highlight the important role of analyst experience and the quality of the information environment in improving earnings forecast accuracy.

3.3. *Recommendation profitability*

Next, we assess stock recommendation profitability as an alternative measure of analyst performance. Analysts who construct research portfolios with higher *IS* are expected to provide more impactful recommendations. Following Huang, Lin, and Zang (2022), we measure stock recommendation profitability (*Rec_pft*) as the market-adjusted buy-and-hold return for a recommended stock, starting one day before the recommendation date and ending at the earlier of 30 days or two days before the analyst *j*'s recommendation for firm *k* is revised or reiterated. Long positions are assumed for buy and strong buy recommendations, while short positions are taken for hold, sell, and strong sell. The stock recommendation profitability sample is about half the size of the earnings per share (EPS) forecast sample. This disparity exists because EPS forecasts are typically mandatory for analysts, whereas recommendations are optional and updated less frequently, generally only in response to significant changes in a stock's outlook. Notably, the mean values for *Psize*, *IS*, and *PCORR* in our stock recommendation profitability sample are 12, 0.135, and -0.003, respectively, which are relatively lower than those in the forecast accuracy sample.

We replace the dependent variable in Eq. (7) with stock recommendation profitability and present the regression results in Table IA3 of the Internet Appendix. For bellwether firms, the coefficients of *IS* in Columns (1) and (2) are positive but not statistically significant. For non-bellwether firms, shown in Columns (3) through (6), the coefficients of *IS* are significantly positive, indicating that higher information share improves analysts' ability to issue profitable recommendations. However, the relation between *PCORR* and recommendation profitability is positive but insignificant, likely since the profitability of stock recommendations is more directly influenced by firm-specific characteristics, such as firm size, return volatility, and trading volume. Furthermore, the coefficients for analysts' firm-specific forecast experience (*Fexp*) and brokerage level (*Topbroker*) are both positive and significant, consistent with the findings on forecast accuracy.

3.4. Career outcomes

The evidence presented so far suggests that a higher information share of the bellwether firm within an analyst's research portfolio is linked to greater accuracy and more profitable recommendations. Along this line, we further hypothesize that analysts who construct informationally efficient portfolios are more likely to achieve favorable career outcomes. To test this hypothesis, we use a logit regression model.

$$\begin{aligned} Star_{j,t+1} = \alpha + IS_{j,t} + Psize_{j,t} + Gexp_{j,t} + Bsize_{j,t} + Accuracy_{j,t} \\ + \text{Firm Controls}_{j,t} + FE + \varepsilon_{j,t+1} \end{aligned}. \tag{8}$$

Variable *Star* is an indicator variable that is one if the analyst is listed on *Institutional Investor* magazine's All-American Research Team in the subsequent year, and zero otherwise. Given that being voted a star analyst represents an exceptional career outcome, we also examine two alternative measures of analysts' career trajectories: *Promotion* and *Fire*. *Promotion* is an indicator variable equals to one if the analyst moves to a high-status brokerage house in the next year, and zero otherwise. Following Hong and Kubik (2003), we define high-status brokerage houses as the top ten brokerage houses employing the largest number of analysts each year, while others are categorized as low-status. To ensure that an analyst's promotion is not influenced by changes in their employer's status, we require that the analyst's previous brokerage house is consistently categorized as low-status in both year *t* and year *t*+1, while the new employer is consistently as high-status in the same period.

Fire is an indicator variable that is one if the analyst moves to a small brokerage house (employing fewer than 25 analysts) or permanently exits the IBES database in the subsequent year. During our sample period, 9.56% of analysts switched brokerage houses annually. Among these, 10.89% were promoted to a more prestigious brokerage house, while 18.53% moved to a small brokerage house or existed, consistent with previous studies (Harford et al. 2019; Hsu et al. 2023).

Our primary variable of interest is portfolio *IS*, which is hypothesized to positively influence analysts' future career outcomes. To account for other factors, we include standard analyst portfolio-level controls and annually average firm characteristics at the portfolio level (Hong and Kacperczyk 2010; Hilary and Hsu 2013). We control for year-fixed effects. In untabulated results, we also measure analyst portfolio *IS* and *Accuracy* over a 3-year period, finding that the significance of the results remains robust.

[Insert Table 5 here.]

Table 5 reports the logit regression results. When regressing one-year-ahead *Star* status on *IS* of an analyst's research portfolio, we find the coefficient of *IS* is 0.598 in Column (1), which is statistically significant at the 10% level. Economically, this coefficient suggests that a one standard deviation increase in *IS* increases the odds of being voted to a star by 6.2%.

When the dependent variable is future *Promotion* to a high-status brokerage, the positive coefficients of *IS* are statistically significant at the 5% level in both Columns (2) and (3). Column (2) focuses on analysts at low-status brokerage houses in year *t*, while Column (3) includes the full sample. Economically, the coefficient in Column (2) indicates that a one standard deviation increase in *IS* raises the odds of an analyst at a low-status brokerage in year *t* moving to a high-status brokerage in year *t*+1by 8.9%.

When the dependent variable in Eq.(8) is *Fire*, the coefficients of *IS* are negative and significant at the 10% level in both Columns (4) and (5). Column (4) uses a restricted sample of analysts at high-status brokerage houses in year *t*, while Column (5) uses the full sample. These findings suggest that analysts with higher *IS* are less likely to face termination.

Regarding the control variables, we find that an analyst's portfolio size and accuracy positively influence the likelihood of attaining star status, moving to a high-status brokerage, and maintaining job security. This highlights the importance of both portfolio quantity and quality for career outcomes. While general research experience supports achieving star status and job stability, it reduces the likelihood of promotion. Furthermore, analysts at larger brokerages are more likely to achieve star status but less likely to be promoted or retain their positions, likely due to limited career advancement opportunities and the more competitive environment within such organizations.

4. Validation tests

In this section, we present additional validation of our methodologies. First, we show that *PCORR* captures holistic economic ties among firms in an analyst's research portfolio. Second, we confirm that the bellwether firm identified using the *PCORR* approach effectively serves as the portfolio's information hub.

4.1. PCORR as an all-in-one measure of economic ties

The *PCORR* approach, originally proposed by Hameed et al. (2015) to identify the bellwether firm in a specific industry, is applied here for the first time in the context of analysts' research portfolios to quantify the strength of economic ties among firms. If effective, *PCORR* should correlate with established economic linkages documented in prior literature.

We examine various types of economic linkages. For within-industry linkages, we use SIC3 (*SIC3peer*) as the baseline to define industry peer relations. Robustness checks are performed using SIC2 (*SIC2peer*), Fama-French 48 (*FF48peer*), and text-based (*TNICpeer*) classifications. Supply-chain linkages are identified via COMPUSTAT customer segment data (*SCpeer*) and text-based vertical product competitors (*VTNICpeer*). Technological peers (*Techpeer*) are identified using Google patent data, and firms headquartered in the same state are classified as geographical peers (*Geopeer*).

[Insert Table 6 here.]

Panel A of Table 6 reports descriptive statistics for firms grouped by economic linkages to bellwethers in research portfolios. The distribution reveals that industry peers are the most prevalent type of linkage, with firms within the same industry consistently showing higher *PCORR* values than those without such ties. Among 496,609 pairs with bellwether firms, 37.7% share the same *SIC3* classification, 49.6% share the *SIC2* classification, and 51.9% share the *FF48* classification.

Regarding supply-chain linkages, COMPUSTAT segment data identifies only 0.7% of firms as actual suppliers or customers of bellwethers. This identification is constrained by self-reporting omissions, coverage limited to listed firms, and imprecise name-based mappings. As a result, *SCpeers* have an average *PCORR* lower than non-*SCpeers*. In comparison, the *VTNIC* approach identifies 24.7% of firms as potential suppliers or customers, although it may misclassify firms without actual linkages. As expected, *VTINCpeers* have a higher average *PCORR* than non-*VTNICpeers*.

We also identify 21.9% of firms as having technical ties with bellwethers, yet these firms exhibit lower *PCORR* than firms without technical ties. Table IA4 in the Internet Appendix suggests that the correlation between *Techpeer* and *SIC3peer* is only 0.07, while the correlation with *VTINCpeer* is higher at 0.15. Martens and Sextroh (2021) also document the endogenous nature of patent citations driven by shared analyst coverage. In addition, 21.1% of firms are identified as geographically linked to bellwethers, and *Geopeers* exhibit higher *PCORR* values than non-*Geopeers*.

We conduct multivariate regressions of *PCORR* on interfirm linkages using yearly firm-pairs between bellwethers and non-bellwethers in analysts' research portfolios. *SIC3peer* represents within-industry linkages, *VTNICpeer* captures potential supply-chain linkages, and *Techpeer* and *Geopeer* for other economic linkages. *T*-statistics are based on standard errors clustered by year and analyst to account for potential correlations (Petersen 2008).

The regression results in Panel B of Table 6 align with the comparisons in Panel A. *SIC3peer* shows a significant positive correlation with *PCORR*, with an *R*-squared of 11.5%, reflecting substantial overlap with industry linkages. *VTNICpeer* and *Geopeer* are also positively correlated with *PCORR*, while *Techpeer* shows a negative correlation, likely due to endogenous intra-firm information flows within analysts' portfolios. These results remain robust in the multivariate regression including all four linkages (Column 5). However, the *R*-squared remains about 12%, suggesting that *PCORR* variations are not primarily attributable to explicit economic linkages. Untabulated tests confirm similar results with alternative measures of economic linkages.

[Insert Figure 2 here]

Therefore, *PCORR* is a comprehensive metric that captures both conventional economic linkages and latent information flows within analysts' research portfolios. To illustrate this, we present two analysts as examples in Figure 2. In this network, the bellwether firm acts as the information hub, connecting other firms through various linkages. The thickness of the edges represents the magnitude of *PCORR*, while the size of the outermost circles indicates each firm's relative market capitalization. Inner circles highlight identifiable linkages to the bellwether. Connections between non-bellwether firms are omitted for clarity.

Figure 2A corresponds to the star analyst discussed in Figure 1. In this structure, IBM, the second-largest firm in the Computer and Office Equipment industry, serves as the portfolio bellwether. All four other firms in the portfolio share SIC3 industry classification and patent ties with IBM, while Apple and HP are also linked through similar product descriptions. These close economic linkages allow the bellwether to account for 38.1% of the total portfolio information, reflecting high informational efficiency.

Figure 2B depicts a "lousy" analyst's portfolio, also with IBM as the bellwether. Although this portfolio including more firms, only a subset has economic ties to the bellwether, with weaker PCORR values and less overlap in linkages. Consequently, the information share of the bellwether is only 20.5%, indicating relatively low informational efficiency for this portfolio.

4.2. Bellwether as the information hub

The firm with the highest average *PCORR* is identified as the bellwether in an analyst's research portfolio. To validate its role as the information hub, we examine earnings announcements by bellwether firms, motivated by Guan, Wong, and Zhang (2015). We expect other firms to react to news from the bellwether, with those having stronger economic ties being more likely to respond. This prediction is empirically tested using a logistic regression.

$$\begin{aligned} Dum\_Rev_{jk} = &\left|SUE_B\right| + DPCORR_{Bk} + \left|SUE_B\right| \times DPCORR_{Bk} + DIS_j \\ &+ \left|SUE_B\right| \times DIS_j + \left|SUE_k\right| + \left|Ret_k\right| + \varepsilon_{jk} \end{aligned}, \qquad (9)$$

where *Dum_REV* is an indicator variable equals one if analyst *j* revises her forecast for firm *k*'s one-year ahead annual earnings within 14 days after any quarterly or annual earnings announcement by the portfolio's bellwether *B*, and zero otherwise. The key variable, $|SUE_B|$, quantifies the magnitude of the bellwether's standardized earnings surprise, calculated as the absolute consensus forecast error scaled by the stock price on the day of the prior earnings announcement. This framework parallels the traditional earnings response coefficient model, where stock returns are regressed on *SUE*. In our study, we examine analysts' responses to earnings news through forecast revisions. If the bellwether acts as the information hub, $|SUE_B|$ should positively influence the likelihood of forecast revisions for other covered firms, implying a positive coefficient of $|SUE_B|$.

We include two dummy variables to capture economic ties and information structure within the portfolio. $DPCORR_{Bk}$ equals one if $PCORR_{Bk}$ exceeds the sample median, and zero otherwise. We hypothesize that stronger economic ties between firm k and the bellwether B increase the likelihood of forecast revisions for firm k, expecting a positive coefficient for $DPCORR_{Bk}$ and its interaction with $|SUE_B|$. Similarly, DIS equals one if the portfolio's IS exceeds the sample median and zero otherwise. Higher IS reflects greater economies of scale in information production within the portfolio. We expect a positive coefficient for $|SUE_B|\times DIS$, indicating its positive influence on forecast revisions.

To account for firm-specific factors, we include $|SUE_k|$, the absolute standardized earnings surprise of firm k's most recent announcement before the bellwether's earnings announcement. We also add $|Ret_k|$, the absolute market-adjusted return of firm k, calculated as the raw return minus the value-weighted market return over the period from analyst j's previous forecast to the bellwether's earnings event date. $|Ret_k|$ controls for firm k's specific news unrelated to the bellwether. We calculate t-statistics using standard errors clustered by year and analyst.

[Insert Table 7 here.]

Panel A of Table 7 examines whether analysts revise their forecasts for other firms in response to the bellwether's earnings announcement. In Column (1), the coefficient of $|SUE_B|$ is significantly positive, and this result remains robust for Columns (2) and (3) under alternative model specifications. This evidence strongly supports the argument that analysts respond to earnings signals from the bellwether by revising forecasts for other firms in their portfolios. The observed information spillover from the bellwether to other firms confirms its role as an effective information hub within the portfolio's structure.

Column (2) includes $DPCORR_{Bk}$ and its interaction with $|SUE_B|$. The significantly positive coefficient of $DPCORR_{Bk}$ (0.018, *t*-value = 2.28) suggests that analysts are more likely to revise forecasts for firms with stronger economic ties to the bellwether, regardless of the magnitude of the earnings signal from the bellwether. The significantly positive coefficient of $|SUE_B|\times DPCORR_{Bk}$ further indicates that analyst's response to the bellwether's signal is stronger when the firm is more closely tied to the bellwether.

In Column (3), the coefficient of *DIS* is significantly positive (0.042, *t*-value = 2.96), indicating that analysts covering informationally efficient portfolios are more likely to revise forecasts for non-bellwether firms following bellwether's earnings announcements. Furthermore, the significantly positive coefficient of $|SUE_B|\times DIS$ suggests that the response coefficient for firms in high-*IS* portfolios (0.913+0.467) is 66% greater than that for firms in low-*IS* portfolios (0.913), indicating a stronger information spillover in informationally efficient portfolios.

We proceed to examine whether the information spillover is unilateral or bilateral by swapping the role of the bellwether and other firms in Eq. (9) and conducting the logistic regression in reverse.

$$\begin{aligned} Dum\_Rev_{jB} = {} & |SUE_k| + DPCORR_{Bk} + |SUE_k| \times DPCORR_{Bk} + DIS_j \\ & + |SUE_k| \times DIS_j + |SUE_B| + |Ret_B| + \varepsilon_{jk} \end{aligned}, \tag{10}$$

where Dum_REV_{jB} is an indicator variable that takes a value of one if analyst *j* revises her forecast for the bellwether's one-year ahead annual earnings within 14 days following a non-bellwether firm *k*'s any quarterly or annual earnings announcement, and zero otherwise. The variables of interest are changed to the $|SUE_k|$ and its interaction terms with $DPCORR_{Bk}$ and *DIS*.

Panel B of Table 7 reports the regression results. First, the coefficient of $|SUE_k|$ is significantly negative in all columns. It suggests that the analyst is less likely to revise the bellwether's forecast in response to other firms' earnings announcements. This result contradicts the argument of information spillover from other firms to the bellwether. We conjecture that the distraction effect (Hirshleifer, Lim, and Teoh 2009) drives this result in that earnings disclosure by non-bellwethers distracts analysts' attention attached to the bellwether. Column (2) further shows that the distraction effect only exists for low-*PCORR* firms. Column (3) shows a significantly positive coefficient for *DIS*, suggesting that analysts would unconditionally increase the likelihood of revising forecasts for bellwether in informationally efficient portfolios.

Overall, the results from Table 7 demonstrate that the identified bellwether serves as an information hub within the research portfolio. Analysts are more likely to revise their forecasts for other firms in response to earnings news from the bellwether, particularly when the bellwether's *IS* is high, and/or their *PCORR* with the bellwether is strong. In contrast, there is no observable revision to the bellwether's earnings forecast in response to other firms' earnings news. The information spillover is unidirectional, flowing from the bellwether to other firms in the research portfolio.

5. Robustness tests

5.1. Alternative PCORR measure based on weekly return correlation

In previous tests, the partial correlation between firms in an analyst's research portfolio is calculated using quarterly ROAs, reflecting firms' historical profitability. As a robustness check, we recalculate the partial correlation using weekly stock returns (*PCORR_Ret*). Since stock returns are forward-looking and incorporate both cash flow and discount rate news, *PCORR_Ret* contains richer information. However, it has two limitations. First, it may be affected by market feedback effects, as Ali and Hirshleifer (2020) demonstrate return momentum among firms sharing analyst coverage. This would induce potential reverse causality issues in analysts' coverage choices. Second, return-based *PCORR* incurs a heavier computational burden than *ROA*-based *PCORR*.

To calculate *PCORR_Ret*, we first use weekly return data from a rolling window of the past 52 weeks to implement a market model similar to Eq. (1) and (2). The subsequent steps align with those used for the ROA-based *PCORR*. Using this return-based measure, we re-identify the portfolio bellwether and re-calculate the corresponding bellwether's information share (*IS_Ret*).

Panel A of Table IA4 in the Internet Appendix presents the correlation coefficients between *PCORR*, *PCORR_Ret*, and various economic linkages measures. *PCORR_Ret* is significantly and positively correlated with ROA-based *PCORR*, though the coefficient is only 0.09, consistent with the conjecture that return-based measures are noisier due to discount rate news. Furthermore, *PCORR_Ret* shows positive correlations with *SIC2*, *SIC3*, *FF48*, and *TNIC* industry classifications, with correlation coefficients higher than those between ROA-based *PCORR* and industry linkages. Additionally, *PCORR_Ret* correlates strongly with geographic proximity and VTNIC supply-chain connections but negatively with COMPUSTAT supplier-customer relationships and technological peers. These patterns are consistent with ROA-based *PCORR* correlations in Table 6.

Variable *IS_Ret* provides an alternative measure of information efficiency in research portfolios. We reestimate Eq. (6) and (7) to examine the impact of return-based *IS* on analysts' forecast accuracy at both portfolio and firm levels. Panel B of Table IA4 in the Internet Appendix reports the regression results. Columns (1) to (4) present the portfolio-level tests, where *IS_Ret* consistently shows a significantly positive coefficient, aligning with the baseline results in Table 3. Furthermore, Columns (5) and (6) focus on firm-level tests for bellwether firms, showing that return-based *IS* significantly enhances forecast accuracy for bellwether firms. Columns (7) to (10) present results for non-bellwether firms, with *IS_ret* exhibiting a significant positive coefficient in all but Column (8), which includes both analyst and firm fixed effects.

Overall, the findings confirm that our main results are robust to alternative *PCORR* and *IS* measures, with both ROA-based and return-based *IS* improving analysts' forecasting performance.

5.2. Impact of various economic linkages on analysts' forecasting performance

Table 4 in Section 3.2 shows that *IS* in analysts' portfolios enhances forecast performance, with non-bellwether firms benefiting more from stronger ties to bellwether firms. To validate these findings, we perform robustness checks by incorporating economic linkage dummies from Section 4.1 and conducting a horse race between *PCORR* and traditional economic linkages. For comparison, we use the binary indicator, *DPCORR* to replace the continuous *PCORR*.

Table IA5 in the Internet Appendix reports the results. First, the positive coefficient of *IS* remains significant across all columns, even after controlling for various economic linkages and fixed effects. This underscores the explanatory power of information share is robust to additional controls. Second, *DPCORR* consistently shows a significant positive coefficient, reinforcing the findings from Table 4. Notably, in Column (1), *DPCORR*'s coefficient (0.018) exceeds that of *SIC3peer* (0.007), indicating that *PCORR*, as a holistic measure of economic ties, outperforms traditional industry linkages like *SIC3peer* in capturing information spillovers.

Regarding supply-chain linkages, the coefficient of *SCpeer* is indistinguishable from zero in all columns highlighting the limitations of identifying supplier-customer relationships using COMPUSTAT sales data. Therefore, we control for *VTNICpeer* in Column (2) and find a significantly positive coefficient of 0.023, indicating that firms with potential supplier-customer relations benefit more from information spillover than those with actual reported relationships.

We find a significantly positive coefficient for *Geopeer* in Columns (1), (2), and

(4). In the baseline setting of Column (1), its coefficient is 0.031, the highest among the four types of economic linkages. This suggests that geographical proximity to the bellwether provides a crucial channel for information spillover in analysts' portfolios, echoing O'Brien and Tan (2015)'s finding that geographical proximity is an important factor in shaping analysts' coverage decisions. Conversely, *Techpeer* has a negative coefficient across all columns, statistically significant in four out of five columns. This result aligns with the negative association between *Techpeer* and *PCORR* in Table 6, suggesting that shared patents do not effectively facilitate the spillover of fundamental information between firms during the same period and might be a consequence of, rather than a driver for, analyst coverage decisions Martens and Sextroh (2021).

5.3. Subperiod by Regulation FD

In October 2000, the Securities and Exchange Commission (SEC) implemented Regulation Fair Disclosure (FD) to reduce selective disclosure and information asymmetry among firms (Heflin, Subramanyam, and Zhang 2003). We hypothesize that, following the introduction of Regulation FD, analysts increasingly rely on information spillovers from portfolio bellwethers to compensate for reduced access to firm managers. To test this, we divide the sample into pre- and post-FD subperiods and perform robustness checks of the firm-level accuracy test in Table 4, controlling for the dummy indicators of economic linkages discussed in Section 4.1.

[Insert Table 8 here.]

Panel A of Table 8 reports the subperiod regression results. Columns (1) and (2) show that before Regulation FD, analysts who construct research portfolios with a higher information share of the bellwether do not demonstrate significantly better forecast performance. In contrast, the coefficients of *IS* in Columns (3) and (4) are significantly positive after Regulation FD. This indicates analysts issue more accurate earnings forecasts when the bellwether firm's information share in their research portfolio is higher. These findings indicate that the restrictions on selective information disclosure imposed by FD have made the economies of scale in information production about the bellwether more critical to sell-side analysts.

5.4. Subsample by brokerage status

Analysts' information production resources are shaped by various factors, including brokerage house's clients and the information shared among colleagues. As a result, analysts' coverage decisions and portfolio information structure differ across brokerage houses. In prestigious brokerages, analysts may prioritize organizational resources over economies of scale.

To empirically test this hypothesis, we divide our sample into high-status and low-status brokerage houses to evaluate the impact of portfolio information sharing on forecast accuracy. Panel B of Table 8 presents subsample analysis results. For the low-status group, the coefficients on *IS* are significantly positive at the 5% level. In contrast, for the high-status group, the coefficients on *IS* are only significant at the 10% level and become insignificant when controlling for other economic linkages. These findings reveal that analysts in low-level brokerage houses rely more extensively on portfolio information sharing and economies of scale in information production.

6. Conclusion

In this paper, we analyze an analyst's research portfolio through the lens of information structure. We use the *PCORR* method to quantify the strength of economic ties among portfolio firms, capturing both traditional and latent economic linkages. By identifying a bellwether as the central information hub, we use the bellwether's information share to measure the economies of scale in information production within the portfolio. Our findings show that analysts who construct research portfolios with higher information share are more skillful, and thus have better forecast performance.

In additional validation tests, we confirmed the relevance of *PCORR* as a holistic measure of the strength of economic ties. The higher *PCORR* is observed for firms with known economic links to the bellwether, which acts as the information hub within the research portfolio. Analysts are more likely to revise their forecasts for other firms in response to significant earnings news from the bellwether, especially when its *IS* and *PCORR* with the bellwether are higher. Conversely, analysts do not revise the bellwether's earnings forecast based on other firms' earnings news.

Overall, our study provides empirical evidence to understand analysts' choices of information production from the cost side. Facing exogenous drivers and constraints in efforts, a financial analyst may extend coverage to firms closely tied to the information hub in the portfolio, and such strategic coverage brings economies of scale in information production about the bellwether firm.

References

Ali, U., and D. Hirshleifer. 2020. Shared analyst coverage: Unifying momentum spillover effects. *Journal of Financial Economics* 136:649-675.

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

Bradley, D., S. Gokkaya, and X. Liu. 2019. The boss knows best: Directors of research and subordinate analysts. *Journal of Financial and Quantitative Analysis* 54:1403-1446.

Bradshaw, M. T. 2012. Discussion of “analysts’ industry expertise”. *Journal of Accounting and Economics* 54:121-131.

Brown, L., A. Call, M. Clement, and N. Sharp. 2015. Inside the ‘black box’ of sell-side financial analysts. *Journal of Accounting Research* 53:1-47.

Chan, K., and A. Hameed. 2006. Stock price synchronicity and analyst coverage in emerging markets. *Journal of Financial Economics* 80:115-147.

Chhaochharia, V., A. Kumar, M. Motahari, and V. Rantala. 2023. Star firms, information externalities, and predictability. *University of Miami Business School Research Paper*.

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

Dessaint, O., T. Foucault, and L. Frésard. 2024. Does alternative data improve financial forecasting? The horizon effect. *Journal of Finance* 79:2237-2287.

Drake, M., P. Joos, J. Pacelli, and B. Twedt. 2020. Analyst forecast bundling. *Management Science* 66:4024-4046.

Groysberg, B., P. M. Healy, and D. A. Maber. 2011. What drives sell-side analyst compensation at high-status investment banks? *Journal of Accounting Research* 49:969-1000.

Guan, Y., M. F. Wong, and Y. Zhang. 2015. Analyst following along the supply chain. *Review of Accounting Studies* 20:210-241.

Guo, Y., and L. Mota. 2021. Should information be sold separately? Evidence from MiFID II. *Journal of Financial Economics* 142:97-126.

Hameed, A., R. Morck, J. Shen, and B. Yeung. 2015. Information, analysts, and stock return comovement. *Review of Financial Studies* 28:3153-3187.

Harford, J., F. Jiang, R. Wang, and F. Xie. 2019. Analyst career concerns, effort allocation, and firms’ information environment. *Review of Financial Studies* 32:2179-

2224.

Heflin, F., K. Subramanyam, and Y. Zhang. 2003. Regulation FD and the financial information environment: Early evidence. *Accounting Review* 78:1-37.

Hilary, G., and C. Hsu. 2013. Analyst forecast consistency. *Journal of Finance* 68:271-297.

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

Hirshleifer, D., S. S. Lim, and S. H. Teoh. 2009. Driven to distraction: Extraneous events and underreaction to earnings news. *Journal of Finance* 64:2289-2325.

Hoberg, G., and G. Phillips. 2010. Product market synergies and competition in mergers and acquisitions: A text-based analysis. *Review of Financial Studies* 23:3773-3811.

Hoberg, G., and G. Phillips. 2016. Text-based network industries and endogenous product differentiation. *Journal of Political Economy* 124:1423-1465.

Hong, H., and M. Kacperczyk. 2010. Competition and bias. *Quarterly Journal of Economics* 125:1683-1725.

Hong, H., and J. D. Kubik. 2003. Analyzing the analysts: Career concerns and biased earnings forecasts. *Journal of Finance* 58:313-351.

Hsu, C., X. Li, Z. Ma, and G. M. Phillips. 2023. Does industry competition influence analyst coverage decisions and career outcomes? *Journal of Financial and Quantitative Analysis* 58:711-745.

Huang, A. H., A. P. Lin, and A. Y. Zang. 2022. Cross-industry information sharing among colleagues and analyst research. *Journal of Accounting and Economics* 74:101496.

Ivković, Z., and N. Jegadeesh. 2004. The timing and value of forecast and recommendation revisions. *Journal of Financial Economics* 73:433-463.

Jacob, J., T. Z. Lys, and M. A. Neale. 1999. Expertise in forecasting performance of security analysts. *Journal of Accounting and Economics* 28:51-82.

Kadan, O., L. Madureira, R. Wang, and T. Zach. 2012. Analysts' industry expertise. *Journal of Accounting and Economics* 54:95-120.

Kini, O., S. Mian, M. Rebello, and A. Venkateswaran. 2009. On the structure of analyst research portfolios and forecast accuracy. *Journal of Accounting Research* 47:867-909.

Kogan, L., D. Papanikolaou, A. Seru, and N. Stoffman. 2017. Technological innovation, resource allocation, and growth. *Quarterly Journal of Economics* 132:665-712.

Luo, S., and N. Nagarajan. 2015. Information complementarities and supply chain analysts. *Accounting Review* 90:1995-2029.

Martens, T., and C. J. Sextroh. 2021. Analyst coverage overlaps and interfirm information spillovers. *Journal of Accounting Research* 59:1425-1480.

O'Brien, P. C., and H. Tan. 2015. Geographic proximity and analyst coverage decisions: Evidence from IPOs. *Journal of Accounting and Economics* 59:41-59.

Petersen, M. A. 2008. Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies* 22:435-480.

Phillips, G. M., G. Hoberg, L. Frésard, and F. Cornelli. 2020. Innovation activities and integration through vertical acquisitions. *Review of Financial Studies* 33:2937-2976.

Ramnath, S., S. Rock, and P. Shane. 2008. The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting* 24:34-75.

Ru, Y., R. Zheng, and Y. Zou. 2024. Public disclosure of private meetings: Does observing peers' information acquisition affect analysts' attention allocation? *Harvard Business School Working Paper*.

Veldkamp, L. 2006. Information markets and the comovement of asset prices. *Review of Economic Studies* 73:823-845.

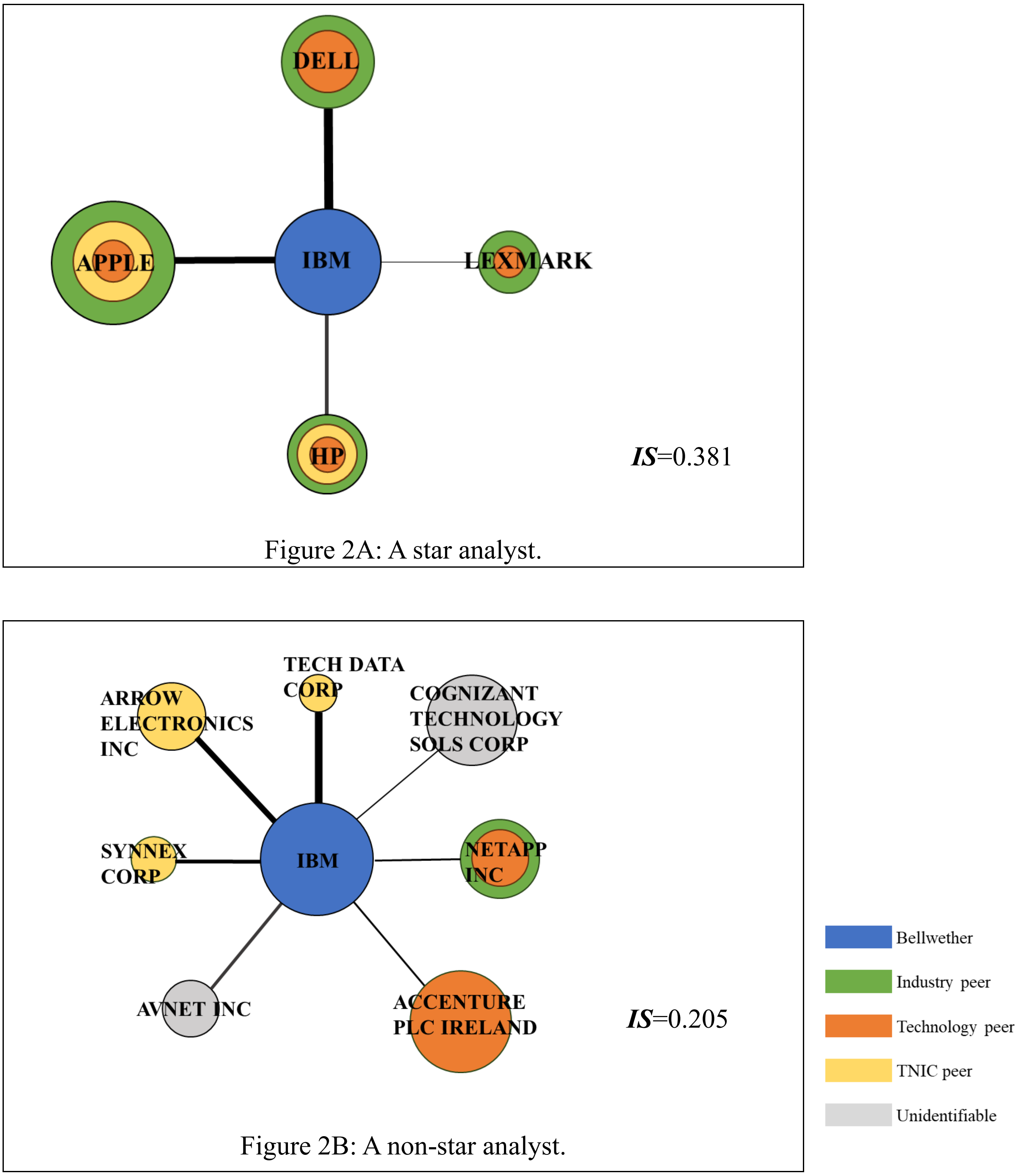
Figures and Tables

Figure 1. Example of information structure

Focal firm i \ Firm k	IBM	DELL	APPLE INC	HP	LEXMARK	***PCORR$_i$***
IBM		0.812	0.222	0.050	0.019	**0.276**
DELL	0.812		0.078	0.065	0.008	**0.241**
APPLE INC	0.222	0.078		0.001	0.021	**0.081**
HP	0.050	0.065	0.001		0.169	**0.071**
LEXMARK	0.019	0.008	0.021	0.169		**0.054**
IS						**0.381**

This figure illustrates the information structure of a sample portfolio managed by a star analyst. It presents a pairwise partial correlation matrix ($PCORR_{ik}$ as defined in Section 2.2) among firms within the research portfolio. The last column of $PCORR_i$ is the average $PCORR_{ik}$ across all other firms k ($k \neq i$) within the analyst portfolio in the row. The firm with the highest $PCORR_i$ is designated as the bellwether within the research portfolio. Information Share (*IS*) contributed by the bellwether is the proportion of its average *PCORR* among the sum over all focal firms.

Figure 2. Identified economic linkages among research portfolio



This figure presents the identified economic linkages between bellwether and other firms within the research portfolio. It depicts the information structure for two analysts covering portfolios with the same bellwether. In each panel, the central firm represents the portfolio's bellwether, and the thickness of the edges connecting the bellwether to other firms reflects their *PCORR* values. The color of circles denotes the type of economic linkage with the bellwether, while overlapping circles indicate firms with multiple types of economic linkages.

Table 1. Variable definitions

Variable	Definition
$PCORR_{i,k,t}$	Partial correlation between firm *i* and firm *k* in year *t*, calculated from a rolling window of quarterly *ROA* regression from year *t*-5 to *t*-1.
$IS_{j,t}$	Information share of analyst *j*'s portfolio bellwether in year *t*, demeaned by average *IS* for portfolios of same size in same year.
$Accuracy_{j,k,t+1}$	Relative forecast error, which is absolute forecast error (*AFE*) for analyst *j* on firm *k* in year *t* adjusted by mean absolute forecast error (*MAFE*) for all analysts covering firm *k* in year *t*, scaled by *MAFE* and multiplied by -1.
Portfolio $Accuracy_{j,t+1}$	Average forecast accuracy of all firms in analyst *j*'s portfolio in year *t* under alternative weighting schemes of equal-weighted (*Accuracy_EW*) or *PCORR* value-weighted (*Accuracy_PCORR*).
$Star_{j,t+1}$	Indicator variable that is 1 if analyst *j* is named in Institutional Investor magazine's All-Star Team in year *t*+1, and 0 otherwise.
$Promotion_{j,t+1}$	Indicator variable that is 1 if analyst *j* is promoted from a low-status to a high-status brokerage house in year *t*+1, and 0 otherwise. Top 10 brokerage houses hiring most analysts are high-status, and others are low-status.
$Fire_{j,t+1}$	Indicator variable that is 1 if analyst *j* moves to a small brokerage house (employing fewer than 25 analysts) or permanently exits the IBES database in year *t*+1, and 0 otherwise.
$Dum\_Rev_{j,k,t}$	Indicator variable that is 1 if analyst *j* revises firm *k*'s earnings forecast within 14 days after bellwether announces earnings, and 0 otherwise.
Analyst-Portfolio level Controls	
$Psize_{j,t}$	Analyst *j*'s portfolio size, measured by number of firms covered in year *t*.
$Gexp_{j,t}$	Analyst *j*'s general experience, measured by number of years since first appearance in I/B/E/S.
$Bsize_{j,t}$	Brokerage house size, measured by number of analysts working at analyst *j*'s brokerage house in year *t*.
$Topbroker_{j,t}$	Indicator variable that is 1 if analyst *j* works at a brokerage house that ranks in top 10 based on number of analysts employed in year *t*, and 0 otherwise.
Analyst-firm level Controls	
$SIC3peer_{j,k,t}$	Indicator variable that is 1 if firm *k* has same SIC3 industry classification as analyst *j*'s portfolio bellwether in year *t*, and 0 otherwise.

$SCpeer_{j,k,t}$	Indicator variable that is 1 if firm *k* has supply chain relationship with analyst *j*'s portfolio bellwether in year *t*, and 0 otherwise.
$Techpeer_{j,k,t}$	Indicator variable that is 1 if firm *k* shares patents with analyst *j*'s portfolio bellwether in year *t*, and 0 otherwise.
$Geopeer_{j,k,t}$	Indicator variable that is 1 if headquarters of firm *k* is in same state as analyst *j*'s portfolio bellwether in year *t* by zip code, and 0 otherwise.
$TNICpeer_{j,k,t}$	Indicator variable that is 1 if firm *k* is Text Based Industry Classifications (TNIC) peer of analyst *j*'s portfolio bellwether in year *t*. TNIC (Hoberg and Phillips 2016) is based on similarity of product descriptions from text analysis, and we adopt a granularity similar to 3-digit SIC classification.
$VTNICpeer_{j,k,t}$	Indicator variable that is 1 if firm *k* is Vertical textual network industry relatedness classification (VTNIC) peer of analyst *j*'s portfolio bellwether in year *t*. VTNIC (Phillips et al. 2020) is derived from BEA input-output table descriptions and firms' 10-K disclosures, indicating potential supply-chain relationship. We adopt a 10% granularity.
$Horizon_{j,k,t}$	Log days between analyst *j*'s forecast for firm *k* and its fiscal year end.
$Fexp_{j,k,t}$	Firm-specific experience, measured by number of years since analyst *j* first issued forecast for firm *k* in I/B/E/S.
$Ret_{j,k,t}$	Absolute value of firm *k*'s market-adjusted return, calculated as raw return minus value-weighted market index return, accumulated from analyst *j*'s previous forecast date for firm *k* to firm *i*'s earnings announcement.
Firm-level controls	
$NAnalyst_{k,t}$	Number of analysts issuing earnings forecasts for firm *k* in year *t*.
$Size_{k,t}$	Log market capitalization of firm *k* (in $thousands) at end of year *t*.
$B/M_{k,t}$	Book-to-market ratio of equity for firm *k* at end of year *t*.
$IO_{k,t}$	Percentage of institutional ownership for firm *k* at end of year *t*.
$Volatility_{k,t}$	Standard deviation of firm *k*'s monthly stock returns in year *t*.
$TrdVol_{k,t}$	Log trading volume in thousands of shares for firm *k* in year *t*.
$RD\_intensity_{k,t}$	R&D expense over operating expense for firm *k* in year *t*.
$AD\_intensity_{k,t}$	Advertising expense over operating expense for firm *k* in year *t*.
$Loss_{k,t}$	Indicator variable that is 1 if firm *k*'s earnings are negative in year *t*, and 0 otherwise.
$\|SUE_{k,t}\|$	Magnitude of standardized earnings surprise of firm *k* on earnings announcement, computed by absolute value of analysts' consensus forecast scaled by stock price on last announcement.

Table 2. Summary statistics

This table reports summary statistics for the sample. Panel A reports variables at analyst-portfolio level. Panel B reports variables at analyst-firm level. We report the mean, median, standard deviation, the first (P25) and third (P75) quartile values, and the minimum and maximum values of these variables.

Variable	N	Mean	Std.	Min	P25	Median	P75	Max
Panel A. Descriptive statistics of variables at analyst-portfolio level								
IS_raw	72,199	0.245	0.163	0.003	0.129	0.195	0.319	0.979
IS	72,199	0.001	0.076	-0.576	-0.027	-0.005	0.014	0.818
Accuracy_EW	72,199	-0.019	0.624	-2.389	-0.184	0.115	0.313	1
Accuracy_PCORR	72,199	-0.017	0.709	-2.677	-0.199	0.129	0.359	1
Psize	72,199	14.886	12.148	3	9	13	18	366
Gexp	72,199	10.482	8.701	0	3	9	16	41
Topbroker	72,199	0.493	0.491	0	0	0	1	1
Bsize	72,199	56.778	53.679	3	20	43	82	329
Star	61,140	0.041	0.199	0	0	0	0	1
Promotion	72,199	0.025	0.203	0	0	0	0	1
Fire	72,199	0.161	0.371	0	0	0	0	1
Panel B. Descriptive statistics of variables at analyst-firm level								
$PCORR_{Bk}$	496,609	0.214	0.220	0	0.039	0.134	0.330	0.999
Accuracy	496,609	0.023	0.957	-3.827	-0.230	0.167	0.569	1
Rec_pft	289,570	0.019	0.147	-3.526	-0.044	0.012	0.075	4.849
SIC2peer	496,609	0.496	0.499	0	0	0	1	1
SIC3peer	496,609	0.377	0.475	0	0	0	1	1
FF48peer	496,609	0.519	0.501	0	0	1	1	1

SCpeer	496,609	0.007	0.083	0	0	0	0	1
Techpeer	481,027	0.219	0.407	0	0	0	0	1
Geopeer	496,609	0.211	0.368	0	0	0	0	1
TNICpeer	455,450	0.407	0.491	0	0	0	1	1
VTNICpeer	455,450	0.247	0.431	0	0	0	0	1
Horizon	496,609	2.084	1.952	1.477	1.771	1.851	2.209	2.525
Fexp	496,609	3.831	4.509	0	1	2	5	41
NAnalyst	496,609	16.669	9.715	2	9	15	23	61
Size	496,609	8.236	1.802	1.056	6.967	8.166	9.467	14.795
B/M	496,609	0.451	0.464	0.094	0.204	0.370	0.605	13.605
IO	496,609	0.555	0.368	0	0.191	0.665	0.856	1.000
Volatility	496,609	0.107	0.062	0.028	0.064	0.091	0.132	0.361
TrdVol	496,609	14.441	1.593	7.060	13.411	14.458	15.509	20.237
RD_intensity	496,609	0.078	0.161	0	0	0	0.096	10.667
AD_intensity	496,609	0.016	0.040	0	0	0	0.014	0.777
Loss	496,609	0.219	0.413	0	0	0	0	1
Dum_Rev	539,655	0.320	0.466	0	0	0	1	1
$\|SUE_B\|$	539,655	0.180	0.416	0	0.019	0.059	0.157	4.957
$\|SUE_k\|$	539,655	0.506	0.702	0	0.048	0.213	0.769	4.997
Ret	539,655	0.063	0.081	0	0.016	0.039	0.080	1.368

Table 3. Analyst forecast accuracy at portfolio level

This table presents impact of portfolio *IS* on analyst's forecast accuracy at portfolio level, estimated using the following regression model:

$$Accuracy_{j,t+1} = IS_{j,t} + Psize_{j,t} + Gexp_{j,t} + Bsize_{j,t} + FE + \varepsilon_{j,t+1}. \quad (6)$$

Dependent variable is analysts' forecast accuracy at portfolio level, which is equally-weighted (*Accuracy_EW*) or *PCORR*-weighted (*Accuracy_PCORR*) of forecast accuracy for all firms in research portfolio in year *t*+1, and firm-level *Accuracy* is proportional mean absolute forecast error. Key independent variable *IS* represents relative information share outflowed from bellwether to the entire research portfolio. Table 1 provides descriptions of other control variables. Year or analyst fixed effects are alternatively controlled, and *t*-statistics reported in parentheses are based on standard errors clustered by year and analyst. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Variables	Accuracy_EW		Accuracy_PCORR	
IS	0.075***	0.067**	0.080***	0.068**
	(2.64)	(2.21)	(2.68)	(1.96)
Psize	-0.002***	-0.001**	-0.001***	-0.001*
	(-4.44)	(-2.30)	(-3.12)	(-1.86)
Gexp	0.003***	0.046	0.003***	0.071
	(10.94)	(0.44)	(10.01)	(0.59)
Topbroker	0.044***	-0.012	0.043***	-0.013
	(9.30)	(-1.59)	(7.91)	(-1.47)
Constant	-0.071***	-0.510	-0.075***	-0.799
	(-12.24)	(-0.44)	(-11.12)	(-0.60)
Year FE	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes
N	72,199	72,199	72,199	72,199
Adj. R^2	0.004	0.159	0.005	0.143

Table 4. Analyst forecast accuracy at firm level

This table presents the impact of portfolio *IS* on analyst's forecast accuracy at firm level, estimated using the following regression model:

$$Accuracy_{j,k,t+1} = IS_{j,t} + PCORR_{Bk,t} + \text{Analyst controls}_{j,t} + \text{Firm controls}_{k,t} + \text{Analyst-firm controls}_{j,k,t} + FE + \varepsilon_{j,k,t+1}. \quad (7)$$

Dependent variable, *Accuracy*, is the proportional mean absolute forecast error for firm *k* in year *t*+1. Key independent variable *IS* represents relative information share outflowed from bellwether to the entire research portfolio. *PCORR* captures the strength of economic ties between non-bellwether firm *k* and the portfolio bellwether in year *t*. Table 1 provides descriptions of other control variables. Year, analyst, brokerage, and bellwether fixed effects are alternatively controlled, and *t*-statistics reported in parentheses are based on standard errors clustered by year and analyst. ∗∗∗, ∗∗, ∗ denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Bellwether		Non-Bellwether					
IS	0.218**	0.180***	0.144***	0.164***	0.207***	0.164***	0.081**	0.206***
	(2.17)	(2.75)	(3.03)	(3.64)	(3.10)	(3.15)	(2.37)	(2.81)
PCORR					0.018***	0.003*	0.008*	0.008**
					(2.86)	(1.70)	(1.73)	(1.97)
Fexp	0.001*	0.001	0.008***	0.000	0.008***	0.000	0.003***	0.007***
	(1.94)	(0.54)	(6.84)	(1.04)	(6.81)	(1.01)	(5.15)	(9.97)
Topbroker	0.029***	0.002	0.046***	-0.002	0.046***	-0.003	0.004	0.047***
	(2.80)	(0.14)	(4.70)	(-0.24)	(4.68)	(-0.25)	(0.39)	(6.07)
Psize	0.005***	0.002	-0.005	-0.001	-0.005	-0.001	-0.000	-0.007***
	(6.04)	(1.19)	(-1.50)	(-0.54)	(-1.51)	(-0.54)	(-0.18)	(-3.37)
Horizon	-0.004***	-0.548***	-0.390***	-0.359***	-0.479***	-0.479***	-0.481***	-0.506***
	(-38.32)	(-32.57)	(-35.07)	(-34.72)	(-33.82)	(-33.97)	(-35.81)	(-33.78)
NAnalyst	0.001**	0.002**	0.000	0.001***	0.000	0.001***	0.000	0.001***

	(2.10)	(2.29)	(1.17)	(4.05)	(1.04)	(3.22)	(0.88)	(2.80)
Size	0.005	0.008	0.002	0.004*	0.006*	0.006*	0.006***	0.002
	(1.17)	(1.48)	(1.03)	(2.01)	(1.89)	(1.89)	(3.23)	(1.50)
B/M	-0.023***	-0.023*	0.003	0.006**	0.003	0.007**	0.010***	0.004**
	(-3.23)	(-1.78)	(1.13)	(2.34)	(1.06)	(2.44)	(3.71)	(1.98)
IO	-0.042***	-0.369***	0.004	-0.006	0.004	-0.006	-0.006	-0.003
	(-5.88)	(-12.15)	(1.22)	(-1.35)	(1.27)	(-1.34)	(-1.54)	(-1.29)
Volatility	-0.004	-0.208**	-0.014	0.017	-0.014	0.018	0.008	0.021
	(-0.10)	(-2.36)	(-0.68)	(1.40)	(-0.66)	(1.53)	(0.61)	(1.47)
TrdVol	-0.004	0.002	-0.003*	0.001	-0.003	0.001	-0.000	0.002
	(-0.93)	(0.42)	(-1.72)	(0.46)	(-1.63)	(0.78)	(-0.26)	(1.62)
RD_intensity	0.011	0.01	0.004	0.037*	0.006	0.038*	-0.006	0.031
	(0.38)	(0.19)	(0.27)	(1.75)	(0.40)	(1.78)	(-0.41)	(1.42)
AD_intensity	0.022	-0.077	-0.022	0.000	-0.019	0.002	0.021	0.022
	(0.25)	(-0.47)	(-0.51)	(0.01)	(-0.45)	(0.04)	(0.53)	(1.17)
Loss	0.005	0.005	0.002	-0.002	0.002	-0.001	0.001	-0.097
	(0.47)	(0.37)	(0.41)	(-0.47)	(0.42)	(-0.40)	(0.16)	(-0.99)
Constant	0.593***	1.581***	0.065	0.049	0.064***	0.059*	0.075***	0.028
	(6.65)	(8.87)	(1.28)	(1.46)	(5.76)	(1.83)	(3.73)	(1.45)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes	No	Yes	No	No
Brokerage FE	No	No	No	No	No	No	Yes	No
Bellwether FE	No	No	No	No	No	No	No	Yes
N	72,199	72,199	496,609	496,609	496,609	496,609	496,609	496,609
Adj. R^2	0.003	0.092	0.003	0.071	0.003	0.072	0.069	0.062

Table 5. Analysts' career outcome

This table presents the impact of portfolio *IS* on analysts' career outcomes using the following logistic regression models:

$$\begin{aligned} Star_{j,t+1} &= \alpha + IS_{j,t} + Psize_{j,t} + Gexp_{j,t} + Bsize_{j,t} + Accuracy_{j,t} \\ &+ \text{Firm Controls}_{j,t} + FE + \varepsilon_{j,t+1} \end{aligned} \quad . \quad (8)$$

Dependent variables, *Star, Promotion* and *Fire*, represent different career outcomes for analysts. Key independent variable *IS* represents relative information share outflowed from bellwether to the entire research portfolio. Table 1 provides descriptions of other control variables. Year-fixed effects are controlled, and *z*-statistics reported in parentheses are based on standard errors clustered by year and analyst. ∗∗∗, ∗∗, ∗ denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	Star	Promotion	Promotion	Fire	Fire
IS	0.598*	0.702**	0.586**	-0.048*	-0.071*
	(1.75)	(2.48)	(2.34)	(-1.72)	(-1.80)
Psize	0.076***	0.024***	0.009*	-0.078***	-0.097***
	(21.68)	(2.67)	(1.73)	(-18.90)	(-33.56)
Gexp	0.058***	-0.020***	-0.001	-0.027***	-0.015***
	(19.41)	(-3.61)	(-0.21)	(-11.87)	(-9.51)
Bsize	0.011***	-0.006***	-0.008***	0.001***	0.001***
	(5.90)	(-5.46)	(-8.04)	(3.68)	(3.68)
Accuracy_EW	0.511***	0.229**	0.020**	-0.418***	-0.6563**
	(7.80)	(1.98)	(2.29)	(-11.22)	(-15.68)
Firm-characteristics	YES	YES	YES	YES	YES
Constant	-10.202***	-4.014***	-6.968***	0.944***	2.704***
	(-23.17)	(-5.64)	(-10.55)	(3.07)	(13.46)
Year FE	Yes	Yes	Yes	Yes	Yes
N	61,140	48,847	72,199	19,421	72,199
Pseudo R^2	0.195	0.064	0.062	0.103	0.251

Table 6. Validating *PCORR* against visible economic ties

This table presents the relationships between *PCORR* and other visible economic ties. Pable A reports the difference in *PCORR* between firms with or without specific economic ties. Panel B presents panel regression results of *PCORR* on other visible economic ties. Table 1 provides descriptions of these economic ties. *T*-statistics reported in parentheses are based on standard errors clustered by year and analyst. ∗∗∗, ∗∗, ∗ denote significance at 1%, 5%, and 10% levels, respectively.

Panel A. *PCORR* difference with or without economic ties

Variables	YES		NO		Diff	
	N	PCORR	N	PCORR	PCORR	T-test
SIC3peer	186,998	0.216	309,611	0.194	0.022	41.406***
SIC2peer	246,509	0.217	250,100	0.188	0.029	48.691***
FF48peer	257,923	0.225	238,686	0.177	0.048	81.163***
TNICpeer	185,275	0.225	270,175	0.186	0.039	69.715***
SCpeer	3,566	0.169	493,043	0.202	-0.033	-9.778***
VTNICpeer	112,698	0.216	342,752	0.197	0.019	27.373***
Techpeer	100,597	0.185	380,430	0.206	-0.021	-30.592***
Geopeer	80,439	0.213	416,170	0.199	0.014	18.825***

Panel B. Regression results of *PCORR* on economic ties

	(1)	(2)	(3)	(4)	(5)
SIC3peer	0.035***				0.023***
	(15.44)				(7.47)
VTNICpeer		0.012***			0.017***
		(3.01)			(4.42)
Techpeer			-0.027***		-0.032***
			(-8.97)		(-10.73)
Geopeer				0.014***	0.016***
				(5.12)	(5.36)
Constant	0.192***	0.212***	0.220***	0.212***	0.206***
	(147.45)	(156.90)	(188.74)	(208.34)	(99.82)
N	496,609	455,450	481,027	496,609	455,450
Adj. R^2	0.115	0.111	0.110	0.111	0.121

Table 7. Analysts' reaction in response to firms' earnings announcement news

This table reports results of analyst-firm-year logistic regression model. Panel A presents whether analyst revises forecasts for firms under coverage in response to bellwether' earnings announcement, estimated using the following model:

$$\begin{aligned} Dum\_Rev_{jk} = &\left|SUE_B\right| + DPCORR_{Bk} + \left|SUE_B\right| \times DPCORR_{Bk} + DIS_j \\ &+ \left|SUE_B\right| \times DIS_j + \left|SUE_k\right| + \left|Ret_k\right| + \varepsilon_{jk} \end{aligned} . \quad (9)$$

Dependent variable is *Dum_Rev*, which indicates whether analyst revises firm's 1-year-ahead annual earnings forecast within 14 days after bellwether announces earnings. Variable of interest is standardized earnings surprise (SUE) of bellwether. *DPCORR* indicates whether firm's *PCORR* with bellwether is higher than median. *DIS* indicates whether portfolio's information share (*IS*) is higher than median. Panel B presents whether analyst revises forecasts for bellwether in response to other firms' earnings announcements, estimated using the following model:

$$\begin{aligned} Dum\_Rev_{jB} = &\left|SUE_k\right| + DPCORR_{Bk} + \left|SUE_k\right| \times DPCORR_{Bk} + DIS_j \\ &+ \left|SUE_k\right| \times DIS_j + \left|SUE_B\right| + \left|Ret_B\right| + \varepsilon_{jk} \end{aligned} . \quad (10)$$

Table 1 provides descriptions of other control variables. *Z*-statistics reported in parentheses are based on standard errors clustered by year and analyst. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Panel A. Non-bellwether's response to bellwether's earnings announcement			
$\|SUE_B\|$	1.151***	1.129**	0.913*
	(3.10)	(2.21)	(1.74)
$DPCORR_{Bk}$		0.018**	
		(2.28)	
$\|SUE_B\|\times DPCORR_{Bk}$		0.045**	
		(2.06)	
DIS			0.042***
			(2.96)
$\|SUE_B\|\times$DIS			0.467***
			(2.63)
$\|SUE_k\|$	6.479***	6.488***	6.464***
	(13.06)	(13.08)	(13.03)
$\|Ret_k\|$	1.190***	1.191***	1.186***
	(22.63)	(22.64)	(22.54)
Constant	-2.026***	-2.035***	-2.048***
	(-212.08)	(-173.23)	(-170.65)
N	539,655	539,655	539,655
Pseudo R^2	0.004	0.091	0.091
Panel B. Bellwether's response to non-bellwether's earnings announcement			

$\lvert SUE_k \rvert$	-5.240***	-4.699***	-4.531***
	(-10.54)	(-6.66)	(-6.86)
$DPCORR_{Bk}$		0.024*	
		(1.76)	
$\lvert SUE_k \rvert \times DPCORR_{Bk}$		-1.047	
		(-1.07)	
DIS			0.024*
			(1.89)
$\lvert SUE_k \rvert \times$ DIS			-1.537
			(-1.57)
$\lvert SUE_B \rvert$	1.113***	1.123***	1.112***
	(2.90)	(2.92)	(2.90)
Ret_B	1.544***	1.546***	1.542***
	(28.27)	(28.29)	(28.22)
Constant	-2.625***	-2.635***	-2.636***
	(-40.31)	(-40.29)	(-40.24)
N	249,486	249,486	249,486
Pseudo R^2	0.034	0.034	0.034

Table 8. Subsample results of analyst forecast performance

This table presents impact of portfolio *IS* on analyst's forecast accuracy at firm level. Dependent variable *Accuracy* is firm's proportional mean absolute forecast error in year *t*+1. Key independent variable *IS* represents relative information share outflow from bellwether to the entire research portfolio. In Panel A, the Pre-Regulation Fair Disclosure (FD) sample period is from 1996 to 2000, the post-FD sample period begins from 2001 to 2023. In Panel B, the top 10 brokerage houses employing the most analysts each year are classified as high-status, while others are deemed low-status. Table 1 provides descriptions of other control variables. Year or analyst fixed effects are alternatively controlled, and *t*-statistics reported in parentheses are based on standard errors clustered by year and analyst. ∗∗∗, ∗∗, ∗ denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Panel A. Regulation fair disclosure				
Variables	Pre_FD		Post_FD	
IS	-0.059	-0.050	0.142**	0.100**
	(-0.92)	(-0.92)	(2.39)	(2.31)
PCORR	-0.003		0.062***	
	(-0.25)		(4.82)	
DPCORR		-0.000		0.015***
		(-0.10)		(2.62)
Economic linkages	No	Yes	No	Yes
Portfolio Characteristics	Yes	Yes	Yes	Yes
Firm Characteristics	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes
Constant	0.550***	0.477***	0.691***	0.484***
	(14.21)	(12.12)	(9.74)	(13.67)
N	84,042	69,750	412,567	411,277
Adj. R^2	0.127	0.103	0.165	0.159
Panel B. Brokerage house status				
Variables	Low-status		High-status	
IS	0.151**	0.140**	0.144*	0.089
	(2.44)	(2.37)	(1.86)	(1.53)
PCORR	0.022***		0.014	
	(3.15)		(1.02)	
DPCORR		0.003		0.006
		(1.28)		(1.15)
Economic linkages	NO	YES	NO	YES
Portfolio Characteristics	YES	YES	YES	YES
Firm Characteristics	YES	YES	YES	YES

Year FE	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes
Constant	2.156***	0.126**	2.295***	0.119**
	(23.71)	(2.20)	(25.66)	(2.71)
N	323,557	308,075	173,052	172,952
Adj. R^2	0.115	0.112	0.099	0.095

Internet Appendix

Table IA1. Bellwether's characteristics

This table presents regression results of analyst research portfolio bellwether on other relative importance variables of the firm. The analyst-firm level logistics regression model is used in Column (1), and ordinary least squares (OLS) regression is used in Column (2). Year or analyst fixed effects are alternatively controlled, and *z*- or *t*-statistics reported in parentheses are based on standard errors clustered by year and analyst. ∗∗∗, ∗∗, ∗ denote significance at 1%, 5%, and 10% levels, respectively.

Variables	(1) Logistics	(2) OLS
Size	0.011***	0.007***
	(2.92)	(7.35)
IO	-0.046	0.00
	(-3.71)	(0.27)
TrdVol	0.024***	0.002**
	(5.80)	(2.06)
Constant	-2.399***	0.076
	(-48.31)	(7.42)
Year FE	Yes	Yes
Analyst FE	No	Yes
N	496,609	496,609
Pseudo/Adj. R^2	0.006	0.015

Table IA2. Alternative *Portfolio Accuracy* measures based on the importance of firms

This table presents impact of portfolio *IS* on alternative analyst's forecast accuracy at portfolio level. Dependent variable is analysts' forecast accuracy at portfolio level, which is firm size-weighted (*Accuracy_Size*), institutional ownership-weighted (*Accuracy_IO*), and trading volume-weighted (*Accuracy_Trdvol*) of forecast accuracy for all firms in research portfolio in year *t*+1, and firm-level *Accuracy* is proportional mean absolute forecast error. Key independent variable *IS* represents relative information share outflowed from bellwether to entire research portfolio. Table 1 provides descriptions of other control variables. Year or analyst fixed effects are alternatively controlled, and *t*-statistics reported in parentheses are based on standard errors clustered by year and analyst. ∗∗∗, ∗∗, ∗ denote significance at 1%, 5%, and 10% levels, respectively.

Variables	(1) *Accuracy _Size*	(2) *Accuracy _Size*	(3) *Accuracy_IO*	(4) *Accuracy_IO*	(5) *Accuracy _Trdvol*	(6) *Accuracy _Trdvol*
IS	0.088**	0.077**	0.148***	0.116***	0.110**	0.090**
	(2.46)	(2.21)	(2.90)	(3.33)	(2.20)	(2.15)
Psize	-0.002***	-0.001**	-0.002***	-0.001***	-0.003***	-0.002***
	(-4.84)	(-2.46)	(-4.09)	(-2.21)	(-5.79)	(-3.37)
Gexp	0.003***	0.048	0.003***	0.018	0.003***	0.036
	(11.41)	(0.45)	(9.00)	(0.14)	(10.45)	(0.29)
Topbroker	0.049	-0.009	0.052***	-0.018*	0.057***	0.013
	(10.15)	(-1.15)	(8.84)	(-1.89)	(10.15)	(1.40)
Constant	-0.073***	-0.534	-0.081***	-0.205	-0.070***	-0.049***
	(-12.29)	(-0.45)	(-11.23)	(-0.14)	(-10.04)	(-0.28)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes	No	Yes
N	72,199	72,199	72,199	72,199	72,199	72,199
Adj. R^2	0.005	0.160	0.003	0.156	0.004	0.141

Table IA3. Analyst recommendation profitability

This table presents impact of portfolio *IS* on analyst's recommendation profitability at portfolio level. Dependent variable *Rec_pft* is the market-adjusted buy-and-hold return for the recommended stock over the period starting from the day before the recommendation date until the earlier of 30 days or 2 days before the recommendation is revised or reiterated. Key independent variable *IS* represents relative information share outflowed from bellwether to entire research portfolio. *PCORR* captures the strength of economic ties between non-bellwether firm and the portfolio bellwether in year *t*. Table 1 provides descriptions of other control variables. Year, analyst, brokerage and bellwether fixed effects are alternatively controlled, and *t*-statistics reported in parentheses are based on standard errors clustered by year and analyst. ∗∗∗, ∗∗, ∗ denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Rec_pft	Rec_pft	Rec_pft	Rec_pft	Rec_pft	Rec_pft
	Bellwether		Non-Bellwether			
IS	0.013	0.03	0.018***	0.009*	0.013**	0.014*
	(1.36)	(0.95)	(3.11)	(1.71)	(2.31)	(1.76)
PCORR			0.001	0.000	0.001	0.001
			(0.50)	(0.05)	(0.53)	(0.69)
Fexp	0.000	0.000	0.000***	0.000**	0.000***	0.000***
	(0.77)	(0.89)	(5.13)	(2.47)	(4.12)	(5.39)
Topbroker	0.002	0.002	0.003***	0.002*	0.002	0.003***
	(1.47)	(0.71)	(5.21)	(1.90)	(1.33)	(3.61)
Psize	0.000**	0.001*	-0.000	0.000**	0.000	0.000
	(2.37)	(1.87)	(-0.45)	(2.56)	(1.13)	(1.48)
NAnalyst	-0.000***	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***
	(-4.05)	(-3.63)	(-5.50)	(-3.16)	(-5.20)	(-3.71)
Size	-0.004***	-0.003***	-0.005***	-0.005***	-0.005***	-0.005***
	(-4.61)	(-2.80)	(-16.26)	(-13.65)	(-14.18)	(-13.45)
B/M	-0.003*	0.000	0.001	0.004***	0.002**	0.005***
	(-1.70)	(0.12)	(1.15)	(5.58)	(2.54)	(5.31)
IO	-0.002	0.002	0.001*	0.002**	0.001*	0.002**
	(-0.90)	(0.53)	(1.81)	(2.08)	(1.75)	(2.08)
Volatility	0.059***	0.046***	0.063***	0.057***	0.063***	0.061***
	(4.61)	(2.74)	(13.11)	(10.95)	(13.03)	(10.79)
TrdVol	0.001	0.002*	0.003***	0.003***	0.003***	0.003***
	(1.53)	(1.92)	(7.99)	(7.56)	(7.89)	(7.55)
RD_intensity	0.020***	-0.030**	0.028***	0.002	0.025***	0.007**
	(3.70)	(-2.57)	(14.43)	(0.74)	(12.24)	(2.04)
AD_intensity	0.008	-0.013	0.023***	0.008	0.023***	0.003
	(0.43)	(-0.45)	(3.09)	(0.85)	(3.04)	(0.29)

Loss	0.003	0.001	0.003***	0.003***	0.003***	0.003***
	(1.24)	(0.42)	(3.99)	(3.52)	(4.10)	(2.70)
Constant	0.027***	0.013	0.015***	0.009**	0.010***	0.008**
	(3.09)	(0.95)	(4.19)	(2.20)	(2.63)	(1.96)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes	No	No
Brokerage FE	No	No	No	No	Yes	No
Bellwether FE	No	No	No	No	No	Yes
N	34,640	34,640	289,570	289,570	289,570	289,570
Adj. R^2	0.009	0.010	0.011	0.026	0.015	0.019

Table IA4. Alternative *PCORR* measure based on weekly return correlation

This table presents impact of an alternative *PCORR* measure based on weekly return correlation (*PCORR_Ret*). Panel A reports the correlation coefficients between *PCORR*_Ret, *PCORR* and other visible economic ties, with the lower triangle displaying the Pearson correlation coefficients and the upper triangle showing the Spearman correlation coefficients. Panel B presents impact of portfolio *IS* based on *PCORR_Ret* on analyst's forecast accuracy. Dependent variable is portfolio-level forecast accuracy in Columns (1) to (4), firm-level forecast accuracy for bellwethers in Columns (5) to (6) and firm-level forecast accuracy for non-bellwethers in Columns (7) to (10). Table 1 provides descriptions of other control variables. Year, analyst, brokerage and bellwether fixed effects are alternatively controlled, and *t*-statistics reported in parentheses are based on standard errors clustered by year and analyst. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Panel A. Correlation coefficients

	PCORR_Ret	PCORR	SIC2peer	SIC3peer	FF48peer	SCpeer	Techpeer	Geopeer	TNICpeer	VTNICpeer
PCORR_Ret	1	0.09***	0.25***	0.23***	0.24***	-0.01***	-0.02***	0.10***	0.27***	0.08***
PCORR	0.09***	1	0.06***	0.05***	0.10***	-0.01***	-0.04***	0.02***	0.09***	0.02***
SIC2peer	0.24***	0.06***	1	0.76***	0.82***	-0.03***	0.06***	0.03***	0.26***	-0.05***
SIC3peer	0.23***	0.05***	0.76***	1	0.68***	-0.01***	0.07***	0.04***	0.27***	-0.07***
FF48peer	0.22***	0.10***	0.82***	0.68***	1	-0.03***	-0.01***	0.01***	0.24***	-0.07***
SCpeer	-0.00***	-0.01***	-0.03***	-0.01***	-0.03***	1	0.04***	0.02***	0.02***	0.04***
Techpeer	-0.02***	-0.05***	0.06***	0.07***	-0.01***	0.04***	1	0.08***	0.07***	0.15***
Geopeer	0.09***	0.02***	0.03***	0.04***	0.01***	0.02***	0.08***	1	0.08***	0.00***
TNICpeer	0.26***	0.09***	0.26***	0.27***	0.24***	0.02***	0.07***	0.08***	1	0.09***
VTNICpeer	0.07***	0.02***	-0.05***	-0.07***	-0.07***	0.04***	0.15***	0.00***	0.09***	1

Panel B. Analyst forecast accuracy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	*Accuracy _EW*	*Accuracy _EW*	*Accuracy _PCORR*	*Accuracy _PCORR*	*Accuracy _Bell*	*Accuracy _Bell*	*Accuracy*	*Accuracy*	*Accuracy*	*Accuracy*

IS_Ret	0.008**	0.125**	0.164***	0.434***	0.390**	0.405*	0.165**	0.011	0.097*	0.112*
	(2.11)	(2.15)	(2.72)	(3.03)	(2.15)	(1.71)	(2.15)	(0.14)	(1.69)	(1.71)
PCORR_Ret							0.009	0.046***	0.012	0.047***
							(0.62)	(4.94)	(1.42)	(5.01)
Psize	-0.033***	-0.013	-0.045***	-0.008	0.004***	0.003***	-0.006**	0.000	-0.000***	-0.006***
	(-7.83)	(-1.31)	(-7.98)	(-0.69)	(5.01)	(3.05)	(-2.15)	(-0.42)	(-2.83)	(-3.71)
Exp	0.003***	0.005***	0.004***	0.006***	0.007***	0.003**	0.009***	0.004***	0.005***	0.009***
	(10.69)	(5.72)	(10.62)	(6.19)	(5.56)	(2.23)	(8.82)	(3.22)	(16.84)	(28.67)
Topbroker	0.002***	0.188***	0.002***	0.189***	0.051***	0.017	0.036***	0.005	0.007	0.030***
	(8.29)	(5.63)	(6.65)	(4.53)	(4.91)	(1.06)	(3.96)	(1.13)	(1.12)	(11.07)
Firm characteristics	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	No	Yes	Yes	No	Yes	No	Yes	No	No
Brokerage FE	No	No	No	No	No	No	No	No	Yes	No
Bellwether FE	No	No	No	No	No	No	No	No	No	Yes
Constant	-0.103***	-2.091***	-0.088***	-2.119***	2.452***	2.459***	2.401***	2.173***	2.174***	2.433***
	(-2.34)	(-5.84)	(-4.93)	(-4.72)	(30.75)	(29.18)	(31.40)	(14.44)	(21.05)	(31.42)
N	67,008	67,008	67,008	67,008	67,008	67,008	489,523	489,523	489,523	489,523
Adj. R^2	0.015	0.014	0.114	0.129	0.107	0.179	0.101	0.153	0.121	0.110

Table IA5. Analyst portfolio information structure and visible economic ties

This table reports the panel regressions of analyst forecast accuracy on *IS*, *PCORR* and other types of economic ties. Year, analyst, brokerage and bellwether fixed effects are alternatively controlled, and *t*-statistics reported in parentheses are based on standard errors clustered by year and analyst. ∗∗∗, ∗∗, ∗ denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
IS	0.248***	0.255***	0.237***	0.214***	0.236***
	(3.76)	(3.99)	(3.79)	(3.28)	(3.80)
DPCORR	0.018***	0.014***	0.013***	0.016***	0.017***
	(3.71)	(3.09)	(2.78)	(3.38)	(3.17)
SIC3peer	0.007**	0.012*	0.006*	0.008**	0.007
	(2.35)	(1.93)	(1.77)	(2.07)	(1.52)
SIC2peer		0.006**			
		(1.99)			
FF48peer		0.038**			
		(1.96)			
SCpeer	0.010	0.008	-0.006	0.007	0.002
	(0.68)	(0.49)	(-0.47)	(0.46)	(0.17)
Techpeer	-0.024***	-0.015**	-0.004	-0.009**	-0.014***
	(-3.82)	(-2.63)	(-1.17)	(-2.23)	(-3.00)
Geopeer	0.031***	0.011**	-0.003	0.032***	0.003
	(5.22)	(2.13)	(-0.48)	(5.53)	(0.63)
TNICpeer		0.002			
		(0.40)			
VTNICpeer		0.023***			
		(3.69)			
Firm characteristics	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	No	Yes	No	No
Broker FE	No	No	No	Yes	No
Bellwether FE	No	No	No	No	Yes
Constant	1.542***	1.496***	1.298**	1.312***	1.523***
	(3.55)	(3.57)	(2.30)	(2.69)	(3.02)
N	496,609	455,450	455,450	455,450	455,450
Adj. R^2	0.105	0.108	0.162	0.125	0.116