When Public Information Goes Private: Analyst Careers and Market Efficiency*

Ling Cen† Jing Chen‡ Chayawat Ornthanalai§ Christoph Schiller¶

CUHK Peking University of Toronto Ohio State

February 23, 2026

Abstract

This paper studies how the exit of equity analysts from public-facing sell-side roles affects investment behavior, price efficiency, and the firm-level information environment. Using a novel dataset tracking analyst career transitions and employer characteristics, we show that analysts who join buyside institutions tend to be more accurate and influence portfolio allocation in stocks they previously covered. Despite this, price efficiency deteriorates following analyst exits, especially for complex or thinly covered firms. We also find increased earnings surprises and greater forecast dispersion. The results highlight a tradeoff between private gains and public costs in the production of financial information.

Key Words: Analyst careers, buy-side institutions, price efficiency, information environment

JEL Codes: G14, G23, J44, M41

*Financial support from the Social Sciences and Humanities Research Council (SSHRC) of Canada is gratefully acknowledged. The paper was previously circulated under the title "Navigating Wall Street: Career Concerns and Analyst Transitions from Sell-Side to Buy-Side".

†Chinese University of Hong Kong. E-mail: Ling.cen@cuhk.edu.hk

‡Peking University. E-mail: mailto:cjing@pku.edu.cn

§University of Toronto. E-mail: chay.ornthanalai@rotman.utoronto.ca

¶Ohio State University. E-mail: schiller.96@osu.edu

1 Introduction

Equity analysts play a critical role in the production and dissemination of information in financial markets. By synthesizing firm disclosures, engaging with top executives, and producing firm-specific research, they provide an important public good: widely available information for a broad audience that informs investment decisions and shapes stock prices (e.g., Hong et al., 2000; Chan and Hameed, 2006; Crawford et al., 2012; Muslu et al., 2014, Birru, Gokkaya, Liu, and Stulz, 2022). Through these channels, analyst research may not only influence asset prices but real outcomes such as executive compensation and corporate investment efficiency (e.g., Bond et al., 2012; Goldstein, 2023).

In recent years, several top-performing sell-side analysts have left traditional brokerage firms to take positions at hedge funds, private equity firms, and other institutional investors. For instance, Mary Meeker, the "Queen of the Net" and a longtime internet analyst at Morgan Stanley, left the firm in 2010 to become a venture capitalist at Kleiner Perkins.[1] These analyst career transitions raise a fundamental question: what are the consequences for information dissemination and market efficiency when the production of expert information moves from a public to a private setting?

Theoretically, the answer is ambiguous. On one hand, sell-side research serves as a central information source for a wide range of market participants. Analysts maintain close relationships with corporate executives (Soltes, 2014; Brown et al., 2015; Li et al., 2024), play a prominent role in earnings calls attended by thousands of investors (Mayew, 2008; Mayew et al., 2013; Matsumoto et al., 2011; Green et al., 2014), and broadly disseminate their reports through client channels and financial media (Irvine et al., 2007; Mikhail et al., 2007; Christophe et al., 2010; Cao et al., 2020). On the other hand, analysts who join buy-side firms may be able to implement their insights more directly through investment decisions, potentially *improving* the speed and accuracy with which information is incorporated into prices. Moreover, recent work questions the continued relevance of sell-side analysts in an era of algorithmic trading and social media (e.g., Gregoire and Martineau, 2022; Jame et al.,

[1] According to a survey on *eFinancialCareer.com* by the recruitment firm Odyssey Search Partners, the most desired career path for sell-side analysts is a move to a private equity investment firm, followed by a hedge fund and then a possible move to a start-up company.

2022; Christensen et al., 2025; Cookson et al., 2025), or argues that analyst research primarily serves to promote brokerage relationships with corporate clients (e.g., Michaely and Womack, 1999; Cowen et al., 2006).

In this paper, we investigate these issues by studying three main research questions. First, what types of analysts are more likely to exit the sell-side for the buy-side or other private-sector roles? Second, how do these analysts influence the portfolio allocation decisions of the buy-side firms that hire them? Third, how do these shifts from public to private information production and dissemination affect stock price efficiency?

To answer these questions, we construct a new dataset that tracks analyst careers by combining departures from I/B/E/S with post-sell-side career outcomes and detailed personal characteristics obtained from LinkedIn, FINRA, and CapitalIQ, among other data sources. We merge this information with quarterly institutional portfolio holdings and stock-level data to study how analyst transitions affect investment outcomes and price efficiency.

Our first main finding is that analysts who exit I/B/E/S to join buy-side institutions such as mutual funds or asset management firms tend to have similar or better forecasting accuracy than their peers.[2] Earlier studies have suggested that analysts who disappear from I/B/E/S tend to underperform (e.g., Mikhail et al., 1999; Hong et al., 2000; Hong and Kubik, 2003), which would imply that their exits may have limited implications for market efficiency. However, the labor market for analysts has changed substantially since those early studies. For example, the number of 13F-filing institutions has grown much faster than the number of I/B/E/S-brokerages since 2000, potentially reflecting the promise of more direct involvement in investment decisions, greater long-term compensation, and better work-life balance (Cheng et al., 2006; DeChesare, 2016). Our new evidence shows that analysts hired by buy-side institutions tend to have stronger forecasting skill—implying potentially meaningful effects on market outcomes.

We directly examine this implication in our second set of tests. Specifically, we ask whether skilled analysts bring valuable information with them, and whether buy-side firms actively trade on that information. To test this, we hand-match the buy-side firms that hire

[2] In contrast, analysts who join non-financial corporations or other sell-side firms exhibit lower average forecast accuracy, consistent with Hong et al. (2000).

former sell-side analysts to institutional portfolio holdings from LSEG (formerly Thomson Reuters). In a difference-in-differences analysis, we find that buy-side firms significantly increase their holdings of the stocks previously covered by newly hired analysts (i.e., treated stocks) after the career transition, relative to stocks covered by control analysts who remain on the sell-side. This effect appears on both the extensive margin (new stock positions) and the intensive margin (larger allocations to existing positions), and is economically meaningful. For example, the number of shares held in treated stocks by buy-side firms increases by approximately 24% in the 8 quarters following the hire. These results are robust to alternative measures of portfolio holdings and are strongest in the 2–3 quarters immediately after the analyst's departure. This finding remains robust when we include buy-side firm-by-year-quarter fixed effects, accounting for any time-varying characteristics at the buy-side level.

We further explore heterogeneity in this effect. The increase in portfolio weights is larger when buy-side firms hire more accurate and optimistic analysts, and for stocks with thinner analyst coverage and higher firm complexity. Despite these changes in portfolio holdings, we find no evidence that hiring ex-sell-side analysts improves overall buy-side performance: both returns and AUM remain flat relative to untreated investment firms. Finally, we find that analysts are significantly more likely to be hired by buy-side firms that already hold at least one of their previously covered stocks, suggesting that employers actively select analysts for their stock-specific expertise. Together, these findings point to a direct channel through which public information producers affect private investment decisions after leaving the sell-side.

Third, we examine the implications of analyst career moves for market efficiency. If the loss of publicly available analyst research reduces the amount of information accessible to the broader market (Martens and Sextroh, 2021), we would expect prices to become less efficient following a sell-side exit. Indeed, we find evidence consistent with this channel: when analysts exit the sell-side—regardless of destination—we observe declines in several standard measures of market efficiency, including increased Amihud (2002) illiquidity, greater Hou and Moskowitz (2005) price delay, and higher return variance ratio inefficiency (Morck et al., 2000; Griffin et al., 2010). These effects are particularly pronounced for analysts who previously covered thinly followed or harder-to-analyze stocks.

In line with these results, we also find that the information environment surrounding covered firms deteriorates following analyst exits. Average earnings surprises increase, the dispersion across analyst forecasts widens, and average analyst coverage declines—suggesting that departing analysts are not fully replaced and that their exits reduce the accuracy, coordination, and reach of available earnings guidance.

Importantly, when focusing on two specific aspects of price efficiency—price *informativeness* measured using the future earnings-to-price sensitivity measure (τ_λ) of Dávila and Parlatore (2021) and private- vs public information dissemination using the Price-Jump Ratio (PJR) measure of Weller (2018)—we find nuanced results depending on the analyst's post-sell-side destination. Specifically, when analysts join other financial sector firms, i.e., either buy-side or non-I/B/E/S sell-side firms, we do not observe significant declines in either price informativeness τ_λ or PJR. In contrast, when analysts transition to non-finance industry roles, such as investor relations or consulting positions, we find statistically and economically significant deterioration in both τ_λ and PJR. This is consistent with the idea that when analysts continue to participate in price discovery, either directly by providing publicly available equity-research or indirectly by influencing private investment decisions, their information production continues to affect price discovery.

Our paper contributes to several strands of the literature. First, we contribute to the literature on the labor market of equity analysts. Early research has suggested that analysts exit IBES primarily because the analysts underperform their peers with respect to forecasting accuracy (e.g., Mikhail et al., 1999; Hong et al., 2000; Hong and Kubik, 2003). In contrast, we provide new evidence that a significant share of analysts leave the sell-side for buy-side and private sector roles, and that those analysts exhibit on average stronger forecasting performance. This finding complements recent research showing that analysts with access to top CEOs are more likely to leave the sell-side for the buy-side (Cen et al., 2021), and that analysts with prior industry experience produce more accurate forecasts and are more likely to receive "All-Star" awards (Bradley et al., 2017). We extend this literature by showing that buy-side firms actively select former sell-side analysts based on firm-specific expertise and demonstrated forecasting skill.

Second, we show that analyst research affects real investment decisions even after analysts exit their sell-side roles. While Birru et al. (2022) document that institutional investors react to analysts' short-term trade ideas, we provide novel evidence that buy-side firms act on analyst insights through longer-term portfolio allocations—specifically, by increasing exposure to stocks previously covered by the analysts they hire. This result indicates that analyst knowledge remains relevant even after formal coverage ends, and that institutional investors leverage this knowledge in investment allocation decisions. Our findings contribute to the broader literature on the economic consequences of analyst research. For example, Li and You (2015) show that analyst coverage enhances investor recognition, Clarke et al. (2007) find that job moves by all-star analysts attract media coverage and investment banking deal flow, and Harford et al. (2019) show that analysts allocate effort to firms where their coverage is most valued.

Third, to the best of our knowledge, we are the first paper to examine the implications of public vs. private information production for market efficiency. While prior research has studied the effect of sell-side analyst coverage on stock price efficiency (e.g., Crawford et al., 2012; Muslu et al., 2014), we examine what happens when expert information producers exit public forums and join private investment firms. We find that stock-level measures of price efficiency deteriorate following a sell-side analyst's departure, suggesting that analysts' contributions to public price discovery are not easily replaced. However, measures of price informativeness, such as the forward-looking earnings-to-price sensitivity of Dávila and Parlatore (2021), only decline when analysts exit the financial sector altogether. This pattern suggests that analysts continue to contribute to price informativeness through investment decisions on the buy-side, rather than by providing information to a broader public audience. Our findings shed new light on the role of analysts as producers of public information and clarify the broader implications of their mobility for price efficiency and market transparency.

The remainder of the paper is structured as follows. Section 2 describes our data and sample construction. Section 3 examines the effect of analyst forecasting accuracy on I/B/E/S exits. Section 4 discusses our findings on effect of analyst transitions on buy-side holdings. Section 5 studies price efficiency effects following sell-side exits. Finally, Section 6 concludes.

2 Data and Summary Statistics

2.1 Analyst Careers

We construct a novel sample of equity analyst careers for analysts covering US listed companies between 2007 and 2016. For an analyst to be included in our sample, we require that she must make at least one one-year-ahead (i.e., FY1) earnings forecast in year t and she must have made earnings forecasts covering one or more firms for at least one year in I/B/E/S by the end of year t. This filter ensures that we have sufficient information to compute analyst characteristics prior to their exit from I/B/E/S. After applying this preliminary filter, we start with $34,034$ analyst-year observations in our initial sample between 2007 and 2016.

To track the careers of analysts who exit I/B/E/S during our sample period, we manually search analyst profiles on career websites, i.e., LinkedIn and RelationshipScience, regulator websites (e.g., BrokerCheck by FINRA), and other financial information websites (e.g., Bloomberg, Reuters, CapitalIQ). To avoid potential mismatches, we require three pieces of information on the profile pages, including the name of an analyst, her affiliated brokerage firm in year t, and her job title, are consistent with those provided by I/B/E/S. We also require that the profile page provides enough information to indicate both the name of the new employer and the start date of the first job that the analyst obtains after leaving I/B/E/S. We only consider an analyst's new employment that is obtained within one year after their last forecasts were reported in I/B/E/S. We impose this maximum one-year transition gap to ensure a meaningful economic association between analyst characteristics before their forecast terminations and their new employments. Whenever available, we systematically obtain information on education degrees, employers, positions/titles, and the start and end time of each employment from LinkedIn for each analyst.[3]

We merge this data with analyst characteristics, their brokerage affiliations, and firms' earnings announcements from I/B/E/S. Following Hong and Kubik (2003) and Clement and Tse (2005), we compute analyst characteristics based on one-year-ahead forecasts (i.e., FY1), which are the most common forecasts made by sell-side analysts. For forecast accuracy,

[3] Our sample period starts from 2007 because information sources above typically do not have a good coverage of career information in earlier period.

boldness, and optimism, we calculate these measures based on the last forecast that an analyst issues before each fiscal year of a firm.[4]

2.1.1 Analyst Career Transitions

As illustrated in Figure 1, for each analyst we observe in our sample in year t, we broadly group their job outcomes in year $t + 1$ into one of three categories.

In the first category, an analyst continues to work for the same I/B/E/S brokerage firm in the following year. This includes analysts who keep the same positions and analysts who move within the same brokerage firm, e.g., an analyst who is promoted as the head of the research department. Unsurprisingly, this scenario represents almost 80% of all observations in the full analyst-year sample, with $27,221$ analyst-year observations.

In the second category, an analyst moves from one I/B/E/S brokerage firm to another I/B/E/S brokerage firm, e.g., an analyst moves from Morgan Stanley to Goldman Sachs. Hong and Kubik (2003) classify all job turnovers under this scenario as either a "promotion" or a "demotion" depending on whether an analyst is moving to a larger or a smaller brokerage firm relative to their previous employer. As shown in Figure 1, we classify $2,192$ observations in our sample period as within-IBES job turnovers.

In the third category, an analyst moves from an I/B/E/S brokerage to a firm, an institution, or an organization not covered by I/B/E/S. In this paper, we refer to this scenario as an analyst "exits" or "leaves" I/B/E/S, as the forecasts of this analyst are "terminated" by I/B/E/S. The new employer can be a boutique sell-side firm not covered by I/B/E/S, a buy-side financial institution, a non-financial corporation, a university or a government organization. Figure 1 shows that we identify $4,621$ such I/B/E/S-exits in our sample.

Among those, we can identify their previous brokerage affiliations from I/B/E/S for $4,136$ of them, which we require to manually search for analysts on career websites like LinkedIn. Further, job turnovers can be voluntary or involuntary.[5] We identify 106 analyst

[4]We drop forecasts that were issued 415 days earlier or later than their corresponding earnings announcement dates. This filter eliminates stale forecasts, and forecasts that are revised after the earnings announcements.

[5]When an analyst is headhunted by another firm, self-initiates a new job search, or leaves her current brokerage firm to establishes a new firm herself, the job turnover is likely a voluntary one. On the other hand, an analyst can be forced to find a new job when her brokerage firm shuts down for reasons that are

turnovers that are likely driven by brokerage closures.[6] Job turnovers associated with the remaining 3,989 analyst-year observations are likely to be voluntary.

These 3,989 analysts who voluntarily left I/B/E/S brokerage firms are the main focus of this paper. The conservative selection criteria described above in Section 2.1 yield a sample of 2,124 analyst-year observations where the full career history of an analyst that voluntarily moves to a non-IBES institution/firm can be identified.[7]

As shown in Figure 1, we classify new jobs of I/B/E/S exits into four categories: (1) sell-side firms that are not covered by I/B/E/S, e.g., independent boutique research firms; (2) buy-side financial institutions; (3) corporate employers, e.g., investors relations jobs; and (4) other jobs, e.g., government agencies, universities and other non-profitable organizations. We further partition buyside employers into four subgroups according to their trading strategies: hedge funds, private equity, and venture capital firms (HF & PE/VC), which are traditionally considered as actively managed funds; mutual funds, pension funds, and asset managers (HF & PE & AM), which are more passively managed; private banks, trusts, and wealth managers (PB & WM), which often invest in alternative assets; and lastly, all other buy-side firms, including endowments/foundations, sovereign wealth funds, and insurance firms.

Among all 2,124 analysts with verified career histories, we find that 730 analysts move to non-IBES sell-side firms, 538 analysts move to the buy-sid, 494 analysts find corporate jobs, and 362 analysts take on other non-financial jobs. Overall, the search results show that moving to buy-side institutions is among the most popular career choice for sell-side analysts after they exit the sell-side industry. Specifically, we find that approximately 25% of analysts join buy-side institutions within one year of exiting I/B/E/S.

2.1.2 Analyst characteristics

Panel 1a of Table 1 provides summary statistics, constructed from I/B/E/S for the 34,034 analyst-year observations in our full turnover sample. As documented, the unconditional

plausibly unrelated to her performance. These job turnovers are likely to be involuntary. These involuntary job turnovers are studied in Cen et al. (2021). We classify turnover as 'involuntary' when the brokerage firm closes within 12 months of the analysts' last forecast on I/B/E/S.

[6]Similarly, we find 97 forced job turnovers driven by brokerage closures in the second category.

[7]The ratio of succesfully identified analysts in our paper is close to 53%, which is consistent with Bradley et al. (2017).

likelihood of an I/B/E/S exit is 13.6% in any given year. Consistent with the literature, the average analyst covers 17 firms in a given year and the average brokerage has 67 analysts in our sample. Approximately 4% of analysts have received an All-Star award, and the average tenure since joining I/B/E/S is 7.5 years in our sample.

2.2 Institutional investor holdings

To study the effect of analyst career moves on investor behavior, we hand-match analysts who join the buy-side, i.e., the 538 analysts in the last row in Figure 1, to institutional investors in the Thomson-Reuters Institutional Holding Database (13f) (now LSEG) based on the name of the buy-side firm. We are able to successfully match 330 analyst-transitions to buy-side firms represented in s34 data. For each s34-institution, we obtain quarterly stock holdings and merge this information with stock trading information, such as stock prices, trading volume, and the number of shares outstanding from CRSP. We use this data to construct quarterly abnormal returns (with respect to Fama-French factors) and assets under management (AUM) for the buy-side firms in our sample.

Panel 1b in Table 1 shows summary statistics at the buyside-portfolio (PF) level at the quarterly frequency. As documented, a given stock in a given quarter has an unconditional likelihood of 13% of being in the average buyside portfolio. The median buyside portfolio comprises of 144 unique stocks, has $1.48 billion in AUM, and earns a quarterly abnormal return of -0.46%.

2.3 Market efficiency and price informativeness

In addition, we construct several measures of market efficiency and stock price informativeness commonly used in the literature. These measures capture different aspects of how efficiently prices reflect information and how easily investors can trade on their insights.

We compute three standard measures of price efficiency using daily return data from CRSP: the return variance ratio (VR) following Morck et al. (2000) and Griffin et al. (2010), the price delay (PD) measure of Hou and Moskowitz (2005), and Amihud (2002) illiquidity (ILLIQ). The variance ratio captures deviations from a random walk, where values below one suggest negative autocorrelation or overreaction, while values above one indicate positive autocorrelation and delayed incorporation of information into prices. We use the absolute deviation of VR from 1 as our measure of price inefficiency. The Hou and Moskowitz (2005) price delay measure captures the extent to which returns are driven by lagged market returns, indicating slow information diffusion. Amihud (2002) illiquidity proxies for transaction costs and trading frictions, with higher values indicating less efficient markets. We aggregate each measure at the annual frequency.

Additionally, we obtain two forward-looking measures of price informativeness introduced in the literature: τ_λ (Dávila and Parlatore, 2021) and the Price-Jump Ratio (PJR) (Weller, 2018). τ_λ captures the sensitivity of stock prices to future earnings, based on predictive regressions of future fundamentals on current market valuations. Intuitively, a high τ_λ value means that stock prices contain a lot of information about a firm's future profitability, implying strong price informativeness. This measure aligns most closely with the notion of "revelatory" price efficiency (Bai et al., 2016), which is key for determining the real effects of information contained in stock prices (Bond et al., 2012; Goldstein, 2023). Further, we obtain the PJR measure, which captures the fraction of large price jumps after earnings announcements relative to all jumps before. A higher PJR suggests that a greater share of information is revealed through public channels, while a lower PJR indicates that more information is impounded gradually or through private channels.

Panel 1c of Table 1 presents summary statistics at the stock-year level. The average VR inefficiency 0.16, with considerable cross-sectional variation (SD of 0.16). The average price delay is 0.25, suggesting that a significant portion of information is incorporated into prices with a lag. On average, stocks are covered by 12.66 analyst in a given year.

2.4 Matched control analysts

To isolate the effects of analyst career transitions on institutional investor portfolios and market efficiency, we construct a matched sample of control analysts. For each treated analyst—defined as one who exits I/B/E/S to join the buyside or another non-I/B/E/S organization—we identify up to four control analysts who remain in sell-side roles for at least three additional years. Control analysts are matched based on the year prior to the treated analyst's exit, using similarity in industry coverage and tenure since joining I/B/E/S. To avoid contamination, we exclude control analysts who work at the same brokerage or cover any of the same stocks as the treated analyst in the matching year. This matched sample allows us to compare changes in institutional holdings and market efficiency for stocks previously covered by treated analysts to a contemporaneous counterfactual of stocks covered by analysts who remain on the sell-side.

3 Who leaves the sell-side—and why?

3.1 Likelihood of analyst turnover

We begin by examining the characteristics of analysts who exit the I/B/E/S database. Previous work has emphasized that poor forecasting performance predicts analyst departures from the sell-side. For instance, Hong et al. (2000) and Hong and Kubik (2003) find that analysts with low forecast accuracy are more likely to disappear from I/B/E/S, interpreting this finding as evidence that analysts primarily leave their brokerages due to poor performance.

However, the career incentives and structure of the equity analyst labor market have changed significantly in recent decades. Buy-side positions increasingly offer greater involvement in investment decisions, higher compensation, and improved work-life balance (Cheng et al., 2006; DeChesare, 2016). Reflecting this shift, the buy-side industry has grown faster than the sell-side over our sample period.[8] As buy-side opportunities have become more attractive, high-performing analysts may exit the sell-side voluntarily to pursue them.

We estimate the following linear probability model, following Hong et al. (2000):

$$\begin{aligned}\mathbb{1}(\text{IBES Exit})_{i,t+1} = \alpha + \beta \text{ Forecast Accuracy Indicator}_{i,t} \\ + \text{Control Variables}_{i,t} + \delta_{b(i)} + \theta_{s(i)} + \mu_t + \epsilon_{i,t+1}.\end{aligned} \quad (1)$$

The dependent variable, $\mathbb{1}(\text{IBES Exit})_{i,t+1}$, is a dummy variable that is equal to one if an analyst who makes earnings forecasts in year t cannot be found in I/B/E/S in $t+1$, and zero

[8]Between 2000 and 2014, the number of 13F filing institutions grew by 82.1%, compared to a 48.6% increase in the number of brokerages in I/B/E/S.

otherwise.[9]. All control variables, including industry fixed effects ($\theta_{s(i)}$), year fixed effects (μ_t), and broker fixed effects ($\delta_{b(i)}$), are constructed identically as those in Hong et al. (2000). Detailed definitions of all control variables are included in Appendix A.

Columns (1) and (2) of Table 2 report our baseline results. *Forecast Accuracy Indicators*$_{i,t}$ are a group of indicator variables that are equal to 1 if an analyst's forecast accuracy falls within the designated percentile range. For instance, 1(0-20%) is equal to 1 if an analyst's forecast accuracy falls between the 0th and 20th percentiles of the entire sell-side analyst population covered by I/B/E/S in year t.

Consistent with Hong et al. (2000), we find that the most accurate analysts are least likely to disappear from the I/B/E/S sample in year $t+1$. As shown in column (1) of Table 2, an analyst in the top 10% of forecast accuracy in year t is 3.07 percentage points less likely to exit I/B/E/S in year $t+1$ relative to other analysts. The effect remains negative and significant—though smaller—for analysts in the 75th-90th percentile (2.13pp) and the 60th-75th percentile (1.07pp). We find a similar pattern in column (2) using alternative accuracy thresholds. In column (3), we replace the percentile indicators with a continuous measure of forecast accuracy, *Accuracy Score*, defined as the percentile rank of an analyst's forecast accuracy. The coefficient remains negative and statistically significant at the 1% level, indicating that lower forecast accuracy in year t predicts a higher likelihood of exiting I/B/E/S in year $t+1$.

The control variables included in Table 2 have the expected sign. For example, we find that analysts covering more firms, analysts 'All-Star' status and with higher seniority at their brokerage firms are less likely to disappear in I/B/E/S sample in the following year. We also find that turnover is higher at larger brokerages with more analysts.

3.2 Analyst transitions to the buy-side

The main focus of this analysis is to understand which analysts leave the sell-side and transition to buyside or other non-sell-side roles. To do so, we repeat the regressions shown in Table 2, but distinguish between the destinations of analysts exiting I/B/E/S. Specifically, following the classification in Figure 1, we construct indicator variables equal to one if an

[9]This variable is defined identically as the *Job Separation* measure in Hong et al. (2000).

analyst exits I/B/E/S and joins a buyside institution, another sell-side firm, a corporate role, or a non-finance job, respectively, and zero otherwise. We then estimate regressions as specified in Equation (1).

The results, summarized in Table 3a, show that "IBES Exit" masks important heterogeneity in analyst turnover. As shown in column (1), analysts with the lowest forecast accuracy, i.e., analysts in the bottom 10% group, are significantly *less likely* to join buy-side firms after exiting IBES, relative to all other analysts in the sample.[10] We also find that analysts with moderate forecast accuracy (60–75th percentile), are relatively more likely to join buy-side institutions after their sell-side careers. Interestingly, analysts in the top decile of forecast accuracy do not show a significantly higher likelihood of moving to the buyside. This may reflect that top performers have already attained star status and strong reputations within their brokerage, reducing their incentive to leave in the first place.

Column (2) of Table 3a indicates that the headline result from Hong et al. (2000), which we replicate for the 2007–2016 period in Table 2, is primarily driven by analysts who leave I/B/E/S to join another sell-side firm. This type of transition is significantly less likely for analysts in the top decile and 75th–90th percentile. By contrast, column (3) shows no systematic relationship between forecast accuracy and the likelihood of moving into corporate roles, such as investor relations or management jobs. Finally, column (4) shows that analysts in the bottom quartile of forecast accuracy—especially those in the bottom 25%—are significantly more likely to transition into non-finance roles, including government or consulting positions. These patterns remain consistent when we apply alternative accuracy thresholds (Appendix Table B1a) or restrict the control group to analysts who remain in I/B/E/S (Appendix Table B1c).

3.3 Heterogeneity in buy-side institutions

To explore heterogeneity in analyst moves to the buy-side, we first split buy-side destinations into large versus small institutions. Table 3b shows that high-performing analysts are significantly more likely to transition to *large* buy-side firms. For example, analysts in the

[10] In fact, using a continuous measure of forecast accuracy in Appendix Table B1b, we a significantly positive effect of forecasting accuracy on the likelihood of moving to a buy-side firm.

top decile of forecast accuracy are 0.66 percentage points more likely to join a large buy-side firm (column 1), relative to the omitted group (40th–60th percentile). In contrast, analysts in the top decile and 75–90th percentile are significantly less likely to join *small* buy-side firms, while good-but-not-great analysts (i.e., those in the 60–75th percentile) are more likely to do so. These patterns suggests that top analysts are particularly attracted to larger, more established buy-side firms. Conversely, as shown in columns (1) and (2), respectively, analysts in the bottom 10% or 10–25% groups are significantly less likely to be hired by large buy-side firms, indicating that lower performance limits access to these desirable exits. Columns (3) and (4) confirm the same pattern using alternative accuracy thresholds.

Next, we examine whether forecast accuracy predicts the type of buy-side institution that analysts join. In line with our classification of buy-side firms in Figure 1, we group buy-side destinations into (i) mutual funds, pension fund, and asset management (MF / PF / AM); (ii) hedge funds, private equity, and venture capital (HF / PE / VC); and (iii) private banks and wealth management firms (PB / WM). Table 3c shows that analyst transitions differ systematically across these categories. Analysts in the top decile of forecast accuracy are significantly more likely to join mutual funds, pension funds, and asset management firms (column 1). In contrast, the top 10% and 75–90th percentile analysts are significantly *less* likely to move to hedge funds or PE/VC firms (column 2). Analysts in the bottom 25% are also significantly less likely to transition to hedge fund and PE/VC roles, indicating that lower performance limits access to these jobs. In contrast, we find that mid-performing analysts (e.g., 60–75th percentile) are significantly more likely to move into private banking and wealth management (column 3). Overall, these patterns suggest that different types of buy-side institutions select analysts on different dimensions of skill and fit.[11]

Taken together, these results highlight that the "Exit from I/B/E/S" label masks meaningful variation in career outcomes—much of it systematically related to forecasting performance. In particular, our findings indicate that analysts who transition to the buy-side do not underperform their peers on the sell-side. On the contrary, analysts moving to large

[11] We uncover similar heterogeneity in the relationship between forecasting accuracy and analyst turnover when examining moves to the sell-side (Appendix Table B1d) and to industry roles (Appendix Table B1e). For example, analysts in the bottom 20% of forecast accuracy are significantly less likely to join finance roles in industrial firms and significantly more likely to return to sell-side positions (broadly defined).

buy-side firms and to mutual funds, pension funds, and asset management firms tend to be among the top performers. This pattern suggests that sell-side analysts bring valuable skills and firm-specific insights that are especially relevant to institutional investors most widely represented in the 13F holdings data. These findings motivate our next analysis: how do institutional investors adjust their portfolios after hiring a former sell-side analyst?

4 Analyst turnover and buy-side investments

As shown in the previous section, analysts who join large buy-side institutions such as asset management firms and mutual funds tend to have higher forecasting performance. If these institutions hire analysts for their stock-specific research and knowledge, we would expect that to be reflected in portfolio holdings—either prior to or following the analyst's transition. Under this scenario, ex-sell-side analysts may continue to contribute to price discovery and market efficiency through the trading activity of their new employers. We directly test this implication in this section.

4.1 Selection on analysts' stock coverage

As detailed in Section 2, we construct a stock-level panel at the quarterly frequency, by hand-matching analysts who exit I/B/E/S and move to the buyside to institutional investors and their quarterly stock holdings data from Thomson Reuters' s34 database. Further, we match each treated analyst, i.e., those that eventually move to the buyside, with up to 4 control analysts based on pre-turnover observables. We begin by examining the cross-sectional relationship between pre-transition analyst coverage and the portfolios of their future employers. Specifically, restrict the quarterly panel to the cross-section observed one year before the analyst turnover, and estimate cross-sectional regressions of the following form on treated and control analysts:

$$\begin{aligned}\mathbb{1}(\text{Move to Buyside})_{i,j,t+1} = \alpha + \beta\ \mathbb{1}(\text{Stock in Buyside PF})_{j,t} \\ + \text{Control Variables}_{i,t} + \delta_{b(i)} + \theta_j + \mu_t + \epsilon_i.\end{aligned} \quad (2)$$

$\mathbb{1}(\text{Move to Buyside})_{i,j,t+1}$ is an indicator variable that takes the value of one if analyst i moves to buyside firm j in the following period, t, $\mathbb{1}(\text{Stock in Buyside PF})_{j,t}$ is an indicator if at least one of the stocks covered by the analyst *before* their exit from I/B/E/S is in the buy-side firm's portfolio. Control variables are similar to Table 2. $\delta_{b(i)}$, θ_j, and μ_t indicate analyst-industry-, buy-side firm-, and year-by-quarter time fixed effects, respectively.

The results in Table 4 show that analysts are significantly more likely to move to an institutional investors when at least one of the stocks they cover is held by the buy-side firm. Column (1) indicates that, prior to transitioning, analysts are 8.1 percentage points more likely to cover stocks held in the future employer's portfolio. This relationship strengthens to 22.6 percentage points in column (2) when buy-side firm fixed effects are included, suggesting that the pattern is not driven by cross-sectional differences across buy-side firms. These findings give a first indication that buy-side firms selectively hire analysts for their firm-specific expertise, which might further affect investment allocation decisions after the job move.

4.2 Effect on buy-side portfolio holdings

Next, we examine the effect of analyst moves from the sell-side to institutional investors on the buy-side on buy-side portfolio holdings using quarterly stock holdings data in a staggered difference-in-differences setting. Specifically, we estimate regressions of the following form,

$$\begin{aligned}\text{Buyside PF}_{s,i,j,t+1} = \alpha &+ \beta_1\ \mathbb{1}(\text{Treated})_{i,j,t} + \beta_2\ \mathbb{1}(\text{Post})_{i,j,t} \\ &+ \beta_3\ [\mathbb{1}(\text{Treated})_{i,j} \times \mathbb{1}(\text{Post})_{i,j,t}] + \delta_s + \theta_j + \gamma_i + \mu_t + \epsilon_{i,t},\end{aligned} \tag{3}$$

where $\text{Buyside PF}_{s,i,j,t+1}$ captures the presence of stock s, previously covered (or not) by analyst i, in the portfolio of buy-side firm j in period $t+1$. $\mathbb{1}(\text{Treated})_{i,j}$ is an indicator variable that take the value of one if analyst i moves to buy-side firm j. $\mathbb{1}(\text{Post})_{i,j,t}$ takes the value of one in time-periods t after analyst i moves to investor j, and zero before. In our most restrictive specification, δ_s, θ_j, γ_i, and μ_t are fixed effects at the stock, buy-side firm, analyst-by-event, and event-time level. Note that, by estimating this as a stacked regression centered around each analyst turnover event, μ_t captures the time (in quarters) relative to the turnover quarter, and γ_i is an event-specific analyst fixed effect. This setting allows us to rule out concerns with standard two-way fixed effects DiD settings recently highlighted in the literature (e.g., Baker et al., 2022). Our main coefficient of interest is β_3, which captures the effect of the job transition on the buy-side portfolio across treated and control analysts, before and after the event. We cluster standard errors at the unit of treatment, i.e., at the analyst and at the buy-side firm ('Mgr') level.

Our baseline tests focus on two outcome variables for Buyside $\text{PF}_{s,i,j,t+1}$: an indicator that takes the value of one if stock s is present in firm j's portfolio (extensive margin), and the log-transformed number of shares s held by firm j (intensive margin). The results are presented in Table 5. As shown in Panel 5a, we find that a given stock that was previously covered by a treated analyst is significantly more likely to be present in the buy-side firm's portfolio after the move, relative to stocks covered by untreated analysts. For example, as shown in column (1), the coefficient estimate for $\mathbb{1}(\text{Treated} \times \text{Post})_{i,j,t}$ indicates that a stock is 1.93 percentage points more likely to be in the buy-side portfolio, which is an increase of 14.8% relative to the sample mean. This estimate is statistically significant at the 5% level and remains similar in magnitude as we include additional fixed effects columns (2) through (5). In our tightest specification in column (5) the fixed effects soak up the unconditional coefficients for $\mathbb{1}(\text{Treated and Post})_{i,j,t}$ and allows us to compare changes over time within a given stock, analyst, and buy-side firm.[12]

We find consistent results on the intensive margin as shown in Panel 5b. As the dependent variable is log-transformed, we can interpret the coefficient estimate for $beta_3$ as the percentage change in the number of shares held by the buy-side firm after the analyst move. Our results indicate that buy-side investors increase the number of shares held—previously covered by the moving analyst—by approximately 24%. Again, the estimate is stable across different fixed effects specifications.

Figure 2 and Appendix Figure 5 show the corresponding dynamics plots, which are constructed by estimating indicators of the time-period relative to the analyst turnover, interacted with the $\mathbb{1}(\text{Treated})_{i,j}$ indicator, in regressions similar to Equation (3). Both at the intensive margin (Figure 2a) and at the extensive margin (Figure 2b) we do not find

[12]The estimated coefficient for $beta_1$ is in line with our finding from Table 4 that treated analysts are more likely to cover stocks in the buy-side firm's portfolio in general. $beta_2$ in column (1) suggests that stock holdings do not systematically increase in the post period in our stacked regression setting.

any evidence of a noticeable pre-trend. The coefficient estimates are flat and statistically indistinguishable from zero in quarters $t = -8$ through $t = 0$ (relative to the analyst turnover). We find the strongest effect in periods $t = 1$ and $t = 2$ after the turnover. In the following periods $t = 3$ through $t = 8$, the effect is still positive, but smaller and statistically insignificant, which might indicate that the impact of ex-sell-side analysts on huy-side portfolios is temporary.[13]

4.3 Robustness of buy-side portfolio results

As shown in Appendix Table B2 our results are robust to alternative ways of measuring buy-side holdings, more granular fixed effects, and stem from effects on the treated- rather than the control analysts. In Panel B2a we split the panel into treated- and control analysts, and estimate the unconditional effect of "Post Turnover" within each subsample. The results show a strong positive effect of $\mathbb{1}(\text{Post})_{i,j,t}$ within the subsample of treated analysts, and a statistically insignificant and small effect within the control subsample. In Panel B2b we use the portfolio weight (i.e., value of stock relative to total portfolio value) in column (1), the percentage of total float of the stock in the buy-side portfolio (column 2), and the dollar-value of the holdings of stock s in the buy-side portfolio (column 3) as alternative measures of buy-side investments. We find similar results as in Table 4. In Panel B2c we augment our specification in Equation (3) with buy-side firm-by-year-by-quarter fixed effects, which controls for any time-varying investor characteristics, such as return performance, AUM in- or outflows, changes in management, etc. The results remain robust.

4.4 Which moves have the biggest effect on buy-side portfolios?

We next explore heterogeneity in the effect of analyst moves on buy-side portfolios in Table 6. Specifically, we median-split analysts into subsamples according to their forecasting accuracy, optimism, and boldness. As shown in Section 3.2, the most accurate analysts are most likely to join large institutional investors, such as asset managers and mutual funds. If forecast accuracy translates into greater influence on investment decisions, we would expect the effect

[13]In alternative fixed effects specifications in Appendix Figure 5, we find that the post-turnover effect remains significantly positive, but decreases in magnitude in periods $t = 3$ through $t = 8$.

of analyst turnover on buy-side holdings to be stronger among high-accuracy analysts. The results in columns (1) and (2) of Panel 6a support this hypothesis: the treatment effect is concentrated in the above-median accuracy subsample, and we cannot reject the null of no effect for low-accuracy analysts.

As shown in columns (3) and (4), we also find that more optimistic analysts have a bigger impact on their buy-side employers investment decisions. In contrast, columns (5) and (6) show that analysts with above-median boldness—those whose forecasts deviate more strongly from consensus—have a weaker effect on portfolio holdings. Taken together, these results indicate that the investment relevance of analyst moves is strongest when the analysts are accurate and optimistic, but conservative relative to the consensus.

We next examine whether the effect of analyst transitions on buy-side portfolios varies with the information environment of the covered stocks. Specifically, we test whether former sell-side analysts have a greater impact on buy-side investment decisions when they bring insights about stocks that are harder to analyze or less efficiently priced. We split the sample at the median along three dimensions, measured in the year prior to the analyst's departure from I/B/E/S: (i) the average analyst coverage of a stock, (ii) its absolute earnings surprise (measured as the standardized difference between mean expected and actual earnings), and (iii) the Herfindahl-Hirschman Index (HHI) of sales across the firm's business segments from Compustat Segment Files.

Panel 6b presents the results. Columns (1) and (2) show that the treatment effect is concentrated among stocks with lower analyst coverage: the coefficient on $\mathbb{1}(\text{Treated} \times \text{Post})$ is 0.0343 and statistically significant at the 1% level for low-coverage stocks, but close to zero and insignificant for high-coverage stocks. Columns (3) and (4) show that the treatment effect is also more pronounced among stocks with higher earnings surprises: the interaction term is statistically significant only in the high-SUE subsample. Finally, columns (5) and (6) explore heterogeneity by firm complexity using the segment-level sales HHI. The effect is significant only for low-HHI firms, i.e., those with more diversified operations.[14]

Taken together, these results suggest that analyst expertise is particularly impactful

[14] The Herfindahl-Hirschman Index (HHI) equals one for single-segment firms. Conversely, a lower HHI implies more diversified revenue streams and thus a more complex operating structure.

in settings where public information is limited—i.e., for less widely covered stocks—and for stocks that are harder to value due to earnings uncertainty or operational complexity.

Lastly, we examine difference at the buy-side firm level. As shown in Panel 6c, we find stronger effects when analysts join buy-side firms with lower past returns (columns 1–4) and lower AUM (columns 5–8), both measured in the year prior to the analyst move. These patterns suggest that transitioning analysts have the greatest impact at lower-performing funds and smaller buy-side firms, which may rely more on external research expertise.

4.5 Effect on buy-side performance

Our previous results suggest that buy-side firms may hire high-performing analysts for their stock-specific expertise, particularly when those analysts cover more complex and less widely followed firms. However, as shown in Figure 2, the impact of these transitions on portfolio holdings appears to dissipate shortly after the move. This raises a natural question: do analysts who transition to the buy-side improve performance outcomes for their new employers? We turn to this question in Table 7.

We estimate difference-in-differences regressions as described in Equation (3) at the institutional investor level and quarterly frequency. We consider three measures of buy-side performance: raw returns, abnormal returns with respect to a 3-factor Fama-French model, and log-transformed assets under management (AUM).

Table 7 reports the results. Across columns (1)—(4), we find no consistent evidence that analysts who move from the sell-side materially improve the performance of their new employers. The interaction term for $\mathbb{1}(\text{Treated} \times \text{Post})$ is small and statistically insignificant for both raw and abnormal returns.

Columns (5) and (6) examine log AUM as the dependent variable. Many fund managers are incentivized to maximize assets under management, and hiring high-profile sell-side analysts may contribute to that goal. However, we again find no consistent evidence that analyst moves lead to growth in AUM. The coefficient of interest in column (5) is weakly negative and becomes statistically insignificant once we include fixed effects in column (6).

Taken together, these results suggest that while analysts influence buy-side portfolio composition upon joining, there is limited evidence that their arrival translates into improved fund performance or fund inflows.

5 Analyst transitions and stock price efficiency

As documented in Section 3, equity analysts with higher forecasting accuracy are more likely to exit I/B/E/S and join buy-side institutions. If these analysts previously contributed meaningfully to price discovery by disseminating value-relevant information to the broader market (e.g., Birru et al., 2022), their departure from public-facing research roles may reduce the efficiency with which information is incorporated into stock prices. On the other hand, as shown in Section 4, analysts who transition to the buy-side meaningfully impact the portfolio allocations of the investment firms that hire them. From this perspective, their research may continue to inform prices—albeit indirectly—through private investment activity. In this section, we empirically test these contrasting predictions.

To test whether analyst exits affect price efficiency, we construct a stock-year panel by stacking three years of treated and matched control observations around each event e, i.e., around each treated analyst's exit event from I/B/E/S.[15] We then estimate the following difference-in-differences regression at the stock-year level:

$$\begin{aligned}\text{Price Efficiency}_{s,i,t+1} = \alpha + \beta\ [\mathbb{1}(\text{Treated}_i) \times \mathbb{1}(\text{Post})_{i,t}] \\ + \delta_s + \theta_{t(e)} + \gamma_i + \mu_t + \epsilon_{i,t+1},\end{aligned} \tag{4}$$

where $\text{Price Efficiency}_{s,i,t+1}$ is one of several measures of price efficiency of stock s, previously covered (or not) by analyst i, in period $t+1$. $\mathbb{1}(\text{Treated})_i$ differentiates between analysts who exit I/B/E/S and their matched controls, while $\mathbb{1}(\text{Post})_{i,t}$ is equal to one for three years after the analyst's exit, and zero before (for both treated and matched control analysts). Hence, the coefficient β captures the average change in price efficiency following analyst exits, relative to the control group. All specifications include stock fixed effects (δ_s), analyst-by-event fixed effects ($\gamma_{i(e)}$), event-time fixed effects ($\theta_{t(e)}$), and calendar year fixed effects (μ_t), which together fully absorb the main effects of treatment and time.

[15]We estimate these regressions at the annual frequency, as most price efficiency measures are available to us at this frequency.

5.1 Full sample of analyst exits

We include three measures of stock price efficiency commonly used in the literature: Amihud illiquidity, Variance Ratio (VR) Inefficiency, and price delay, as detailed in Section 2. Additionally, we consider two measures of stock price informativeness recently introduced in the literature: the first is based on the sensitivity of future earnings to stock prices, i.e., τ_λ from Dávila and Parlatore (2021), and captures how informative prices are for future fundamentals. The second is the Price-Jump-Ratio (PJR) from Weller (2018), which measures the extent to which information is incorporated into prices through private channels, as reflected in price jumps around earnings announcements. We start by estimating the regression in Equation (4) on the full sample of all analyst exits from I/B/E/S, i.e., not considering which job they transition to. The results are presented in Panel 8a of Table 8.

Across columns (1)–(3), we find consistent evidence that analyst departures are associated with a deterioration in overall price efficiency. Specifically, stocks previously covered by analysts who leave the sell-side exhibit higher Amihud illiquidity (column 1), greater variance ratio inefficiency (column 2), and increased price delay (column 3) in the years following the analyst's exit, relative to stocks covered by analysts who remain on the sell-side. These effects are statistically significant and suggest that the loss of publicly available analyst research impairs the incorporation of information into prices. For example, column (1) indicates that VR Inefficiency increases by 3.4% (= 0.0055/0.16) for treated stocks in the post period, relative to the sample mean.

Figures 3a through 3c provide the corresponding dynamics plots for these estimates. All three event-study plots exhibit stable pre-trends followed by a deterioration in price efficiency after the analyst's departure. The rise in Amihud illiquidity and VR inefficiency is large and persistent, while the increase in price delay is smaller and less precisely estimated. Overall, the dynamic effects are consistent with our baseline regression results in Panel 8a and confirm that the loss of public-facing analyst coverage impairs price efficiency.

Next, columns (4) and (5) examine two specific aspects of price informativeness. In column (4), we find a statistically significant decline in τ_λ, indicating that prices become less predictive of future earnings once analysts exit. Our estimates imply a decline in τ_λ of

1.7% (= 0.0051/0.30) relative to the sample mean. Column (5) shows a marginally significant increase in the Price-Jump Ratio (PJR), consistent with more information being impounded into prices through private rather than public channels around earnings announcements.

5.2 Different analyst destinations and price informativeness

Next, we dig deeper into these aspects by examining if our results differ depending on the type of firm an analyst joins after exiting IBES. Specifically, we separatly estimate Euqation (4) for the subsamples of treated analysts who join another sell-side firm, a buy-side firm, or exit the financial sector entirely, i.e., an industry- or government position, respectively, compared to the control analysts who remain on the sell-side, as before. We focus specifically on the effects on forward-looking price informativeness (i.e., τ_λ) and private vs. public price discovery (i.e., PJR), as these measures are most relevant for real outcomes (e.g., Bond et al., 2012; Goldstein, 2023) and the key channel of our paper of information production in public or private settings, respectively.

The results, summarized in columns (1)–(2), (3)–(4), and (5)–(6), respectively, reveal a striking divergence. When analysts exit to other sell-side firms or to buyside institutions, we observe no statistically significant changes in either τ_λ (columns 1 and 3) or PJR (columns 2 and 4). This suggests that when analysts remain within the financial sector, whether in public or private information roles, their research continues to influence price formation—either directly through new publications or indirectly via trading activity.

In contrast, when analysts leave the financial industry altogether (columns 5–6), we find meaningful declines in price informativeness. Specifically, τ_λ declines significantly (column 5), with an estimated effect approximately twice as large as the baseline effect in Panel 8a. Similarly, PJR increases sharply (column 6), roughly doubling the baseline increase in Panel 8a. The corresponding dynamic effect plots in Figure 4 confirm these magnitudes and show that the effects emerge only after analysts exit I/B/E/S, with no evidence of pre-trends. These findings imply that analysts exiting I/B/E/S affect important aspects of price informativeness only when they depart the information production ecosystem altogether.

5.3 Heterogeneous effects on price efficiency

We next examine whether the effect of analyst exits on price efficiency varies across stocks with different information environments. Mirroring our earlier analysis of institutional holdings in Section 4.4, we split the sample based on the complexity and coverage of the firms followed by treated and control analysts. Specifically, Panel 9a reports results from a sample split at the median based on the number of analysts covering each stock prior to the treated analyst's exit from I/B/E/S. We split stocks covered by treated analysts and retain all stocks covered by control analysts in both subsamples.

We find that the decline in price efficiency is concentrated in stocks with low analyst coverage prior to the exit. In this subsample (columns 1–3), we observe economically and statistically significant increases in Amihud illiquidity, variance ratio inefficiency, and price delay. In contrast, for stocks with high pre-exit analyst coverage (columns 4–6), the effects are muted or even reversed. These results are consistent with the notion that the loss of a public information intermediary matters more when fewer alternative information producers are available to support price discovery.

Next, we examine whether the effect of analyst exits on price efficiency is stronger for firms that are more complex and harder to analyze. We consider two dimensions of complexity. First, in Panel 9b, we split the sample by the magnitude of firms' earnings surprises ($|SUE|$), based on the idea that firms with more volatile or unpredictable earnings pose greater challenges for analysts. Second, in Panel 9c, we split firms based on the Herfindahl index of segment sales (HHI), where lower concentration implies greater operational complexity. These partitions are analogous to those used in Section 4.4.

The results indicate that the effects of analyst exits on price efficiency are concentrated in more complex firms. In Panel 9b, we find significant increases in illiquidity and variance ratio inefficiency following the exit of analysts covering firms with high earnings surprises (columns 4–5), but no such effects for firms with more predictable earnings (columns 1–2). Similarly, in Panel 9c, we find that exits affect price efficiency more strongly in firms with low segment concentration (columns 4–5), where analysts arguably add more value by helping market participants understand diverse lines of business. These findings further support the notion that analysts play a particularly important role in sustaining price efficiency when firms are harder to understand.

5.4 Analyst exits and the information environment

In the final part of the paper, we examine how analyst exits from I/B/E/S affect the firm-level information environment. We focus on three outcomes commonly used to assess the quality of analyst coverage (e.g., Brown et al., 2015): the magnitude of earnings forecast surprises, the dispersion of earnings forecasts across analysts, and the number of analysts covering a given stock.

Theoretically, the expected effect is ambiguous. On one hand, analyst exits may reduce forecast accuracy if high-ability analysts leave and the remaining analysts have less informative signals to coordinate around. In particular, prior work shows that analysts tend to herd their forecasts out of reputational concerns (Hong et al., 2000), so the loss of a credible anchor could amplify uncertainty. On the other hand, brokerages may quickly replace departing analysts, and the remaining analysts may reallocate attention or reduce coverage breadth to maintain quality, potentially mitigating the impact of exits.

We estimate regressions similar to Equation (4) at the stock-year level, stacking treated and control analysts over a window of three years before and after each analyst exit event. Table 10 presents the results. Across all three measures, we observe a deterioration in the information environment following analysts' exits from I/B/E/S.

As shown in column (1), the absolute earnings surprise increases by 3.36 percentage points for stocks previously covered by exiting analysts, relative to control stocks. In column (2), we find that forecast dispersion rises significantly after the exit: the standard deviation of EPS forecasts increases by 0.42 percentage points (significant at the 1% level), corresponding to a 4.7% increase relative to the unconditional sample mean of 0.09. This suggests that analysts' departures reduce herding and increase forecast uncertainty among the remaining analysts.

Finally, column (3) shows that analyst coverage declines by roughly 0.45 following an analyst's exit. While this is partially mechanical—removing an analyst naturally reduces coverage by one—it also suggests that brokerages partially—but not fully—fully replace departing analysts in the years that follow. This persistent reduction in coverage may have lasting effects on the firm's information environment and price efficiency.

6 Conclusion

This paper examines how the transition of equity analysts from public-facing sell-side roles to private-sector positions affects investment behavior, price efficiency, and the firm-level information environment. Motivated by the growing trend of experienced analysts leaving traditional brokerages to join hedge funds, asset managers, and non-finance roles, we assess the consequences of this shift for financial markets.

We assemble a novel dataset that tracks analyst exits from I/B/E/S and links them to subsequent employment outcomes and personal characteristics. We find that a substantial share of analysts exit to join buyside institutions, and that these analysts exhibit stronger forecast accuracy than their peers. Buyside firms appear to act on this information: they significantly increase portfolio weights in the stocks previously covered by the analysts they hire. This effect is strongest for more accurate and optimistic analysts, for thinly covered stocks, and when the hiring firm already holds a position in the analyst's prior coverage universe. These patterns suggest that analyst expertise continues to shape capital allocation decisions even after the leave the sell-side.

Despite this, we find that analyst exits reduce price efficiency in public markets. Stock liquidity declines, price reactions become more delayed, and return variance ratio inefficiency rises. These effects are most pronounced for stocks that are harder to analyze—those with fewer analysts, larger earnings surprises, or more complex business operations—and for analysts with narrow industry specialization. Importantly, forward-looking measures of price informativeness only decline when analysts leave the financial sector entirely. When they remain within the industry, either at buyside or other sell-side firms, their information continues to contribute to price formation.

Finally, we show that the firm-level information environment deteriorates after analyst exits: earnings surprises increase, forecast dispersion rises, and overall coverage declines. This suggests that departing analysts are not fully replaced and that their exit leaves a gap in market-facing information.

Taken together, our findings highlight the central role of sell-side analysts in shaping both public and private investment decisions. While their influence often persists after they leave the sell-side, especially when they remain in the financial sector, the broader market suffers when expert information producers exit public forums and are not fully replaced.

References

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

Bai, J., T. Philippon, and A. Savov (2016). Have financial markets become more informative? *Journal of Financial Economics 122*(3), 625–654.

Baker, A. C., D. F. Larcker, and C. C. Wang (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics 144*(2), 370–395.

Birru, J., S. Gokkaya, X. Liu, and R. M. Stulz (2022). Are analyst short-term trade ideas valuable? *The Journal of Finance 77*(3), 1829–1875.

Bond, P., A. Edmans, and I. Goldstein (2012). The real effects of financial markets. *Annual Review of Financial Economics 4*(1), 339–360.

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

Brown, L. D., A. C. Call, M. B. Clement, and N. Y. Sharp (2015). Inside the "black box" of sell-side financial analysts. *Journal of Accounting Research 53*(1), 1–47.

Cao, Y., F. Guan, Z. Li, and Y. G. Yang (2020). Analysts' beauty and performance. *Management Science 66*(9), 4315–4335.

Cen, L., J. Chen, S. Dasgupta, and V. Ragunathan (2021). Do analysts and their employers value access to management? evidence from earnings conference call participation. *Journal of Financial and Quantitative Analysis 56*(3), 745–787.

Chan, K. and A. Hameed (2006). Stock price synchronicity and analyst coverage in emerging markets. *Journal of Financial Economics 80*(1), 115–147.

Cheng, Y., M. H. Liu, and J. Qian (2006). Buy-aide analysts, sell-side analysts, and investment decisions of money managers. *Journal of Financial and Quantitative Analysis*.

Christensen, K., A. Timmermann, and B. Veliyev (2025). Warp speed price moves: Jumps after earnings announcements. *Journal of Financial Economics 167*, 104010.

Christophe, S. E., M. G. Ferri, and J. Hsieh (2010). Informed trading before analyst downgrades: Evidence from short sellers. *Journal of Financial Economics 95*(1), 85–106.

Clarke, J., A. Khorana, A. Patel, and P. R. Rau (2007). The impact of all-star analyst job changes on their coverage choices and investment banking deal flow. *Journal of Financial Economics 84*(3), 713–737.

Clement, M. B. and S. Y. Tse (2005). Financial analyst characteristics and herding behavior in forecasting. *The Journal of Finance 60*(1), 307–341.

Cookson, J. A., M. Niessner, and C. Schiller (2025). Can social media inform corporate decisions? evidence from merger withdrawals. Journal of Finance, Forthcoming.

Cowen, A., B. Groysberg, and P. Healy (2006). Which types of analyst firms are more optimistic? *Journal of Accounting and Economics 41*(1-2), 119–146.

Crawford, S. S., D. T. Roulstone, and E. C. So (2012). Analyst initiations of coverage and stock return synchronicity. *The Accounting Review 87*(5), 1527–1553.

Dávila, E. and C. Parlatore (2021). Trading costs and informational efficiency. *The Journal of Finance 76*(3), 1471–1539.

DeChesare, B. (2016). Investment banking exit opportunities: The myth of the buy-side job. http://www.mergersandinquisitions.com/investment-banking-exit-opportunities.

Goldstein, I. (2023). Information in financial markets and its real effects. *Review of Finance 27*(1), 1–32.

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

Gregoire, V. and C. Martineau (2022). How is earnings news transmitted to stock prices? *Journal of Accounting Research 60*(1), 261–297.

Griffin, J. M., P. J. Kelly, and F. Nardari (2010, 07). Do market efficiency measures yield correct inferences? a comparison of developed and emerging markets. *The Review of Financial Studies 23*(8), 3225–3277.

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

Hong, H. and J. D. Kubik (2003). Analyzing the analysts: Career concerns and biased earnings forecasts. *The Journal of Finance 58*(1), 313–351.

Hong, H., J. D. Kubik, and A. Solomon (2000). Security analysts' career concerns and herding of earnings forecasts. *The RAND Journal of Economics 31*(1), 121–144.

Hong, H., T. Lim, and J. C. Stein (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance 55*(1), 265–295.

Hou, K. and T. J. Moskowitz (2005). Market frictions, price delay, and the cross-section of expected returns. *The Review of Financial Studies 18*(3), 981–1020.

Irvine, P., M. Lipson, and A. Puckett (2007). Tipping. *The Review of Financial Studies 20*(3), 741–768.

Jame, R., S. Markov, and M. C. Wolfe (2022). Can fintech competition improve sell-side research quality? *The Accounting Review 97*(4), 287–316.

Li, G., C. Spence, and Z. Chen (2024). Sell-side analysts as social intermediaries. *Contemporary Accounting Research 41*(3), 1925–1951.

Li, K. K. and H. You (2015). What is the value of sell-side analysts? evidence from coverage initiations and terminations. *Journal of Accounting and Economics 60*(2), 141–160.

Martens, T. and C. J. Sextroh (2021). Analyst coverage overlaps and interfirm information spillovers. *Journal of Accounting Research 59*(4), 1425–1480.

Matsumoto, D., M. Pronk, and E. Roelofsen (2011). What makes conference calls useful? the information content of managers' presentations and analysts' discussion sessions. *The Accounting Review 86*(4), 1383–1414.

Mayew, W. J. (2008). Evidence of management discrimination among analysts during earnings conference calls. *Journal of Accounting Research 46*(3), 627–659.

Mayew, W. J., N. Y. Sharp, and M. Venkatachalam (2013). Using earnings conference calls to identify analysts with superior private information. *Review of Accounting Studies 18*(2), 386–413.

Michaely, R. and K. L. Womack (1999). Conflict of interest and the credibility of underwriter analyst recommendations. *The Review of Financial Studies 12*(4), 653–686.

Mikhail, M. B., B. R. Walther, and R. H. Willis (1999). Does forecast accuracy matter to security analysts? *The Accounting Review 74*(2), 185–200.

Mikhail, M. B., B. R. Walther, and R. H. Willis (2007). When security analysts talk, who listens? *The Accounting Review 82*(5), 1227–1253.

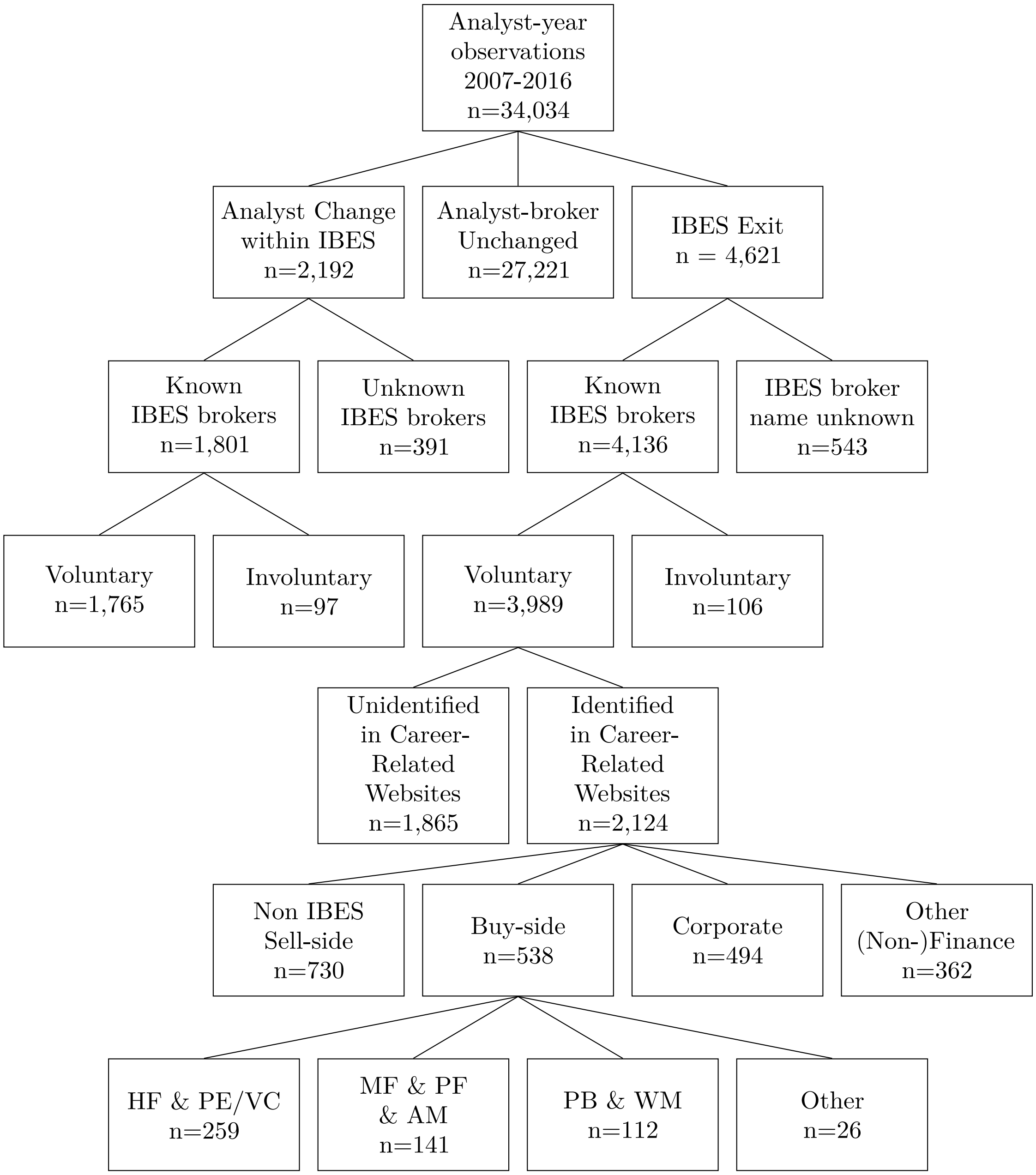
Morck, R., B. Yeung, and W. Yu (2000). The information content of stock markets: why do emerging markets have synchronous stock price movements? *Journal of Financial Economics 58*(1-2), 215–260.

Muslu, V., M. Rebello, and Y. Xu (2014). Sell-side analyst research and stock comovement. *Journal of Accounting Research 52*(4), 911–954.

Soltes, E. (2014). Private interaction between firm management and sell-side analysts. *Journal of Accounting Research 52*(1), 245–272.

Weller, B. M. (2018). Does algorithmic trading reduce information acquisition? *The Review of Financial Studies 31*(6), 2184–2226.

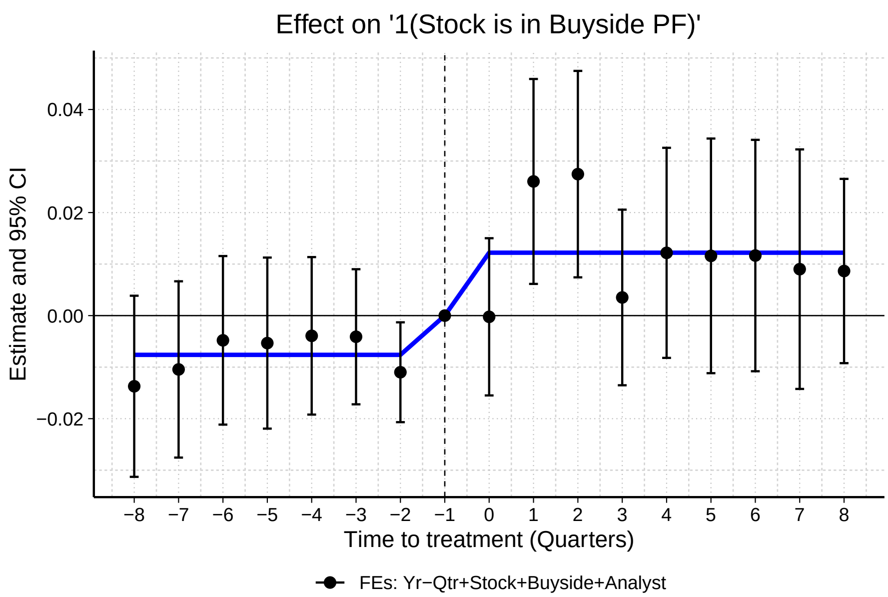
Figure 1: Analyst career transitions



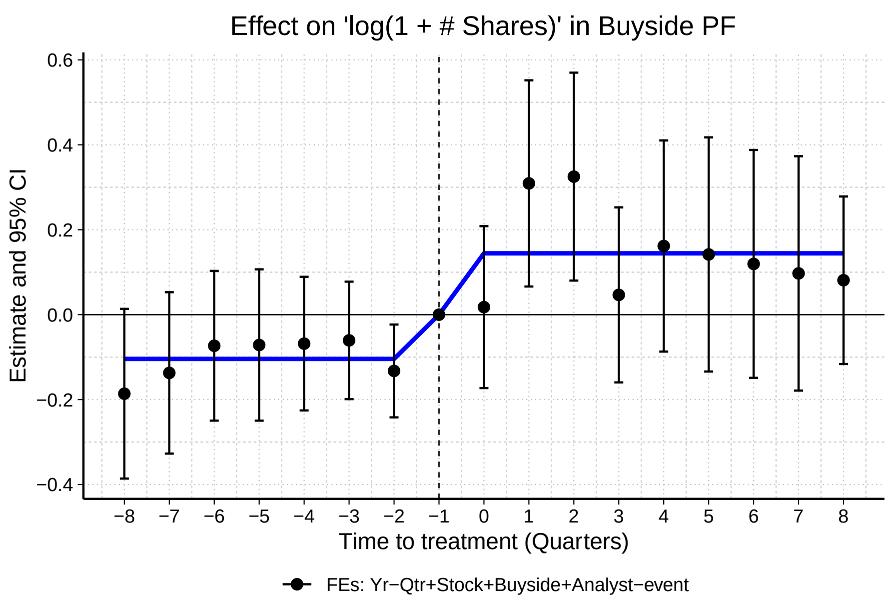
Notes: This figure shows how we track sell-side analysts with at least one year I/B/E/S experience to identify their career turnovers. The number in each node indicates the number of job turnovers in this category. 'Other (Non-) Finance' jobs include Consulting (100), Commercial/Retail/Wholesale Banking (34), Government/Institutions (50), and others (178). Within buy-side jobs, 'HF & PE/VC' indicates the number of sell-side analysts transition to hedge funds or private equity and venture capital firms. 'MF & PF & AM' indicates the number of sell-side analysts who transition to mutual funds, pension funds, or asset management. 'PB & WM' indiactes analysts who move to private banking, trusts, or wealth management. Other includes analysts who join endowments/foundations, sovereign wealth funds, and insurance firms.

Figure 2: Analyst transitions and buy-side holdings

(a) Is the stock in the buy-side firm's portfolio?



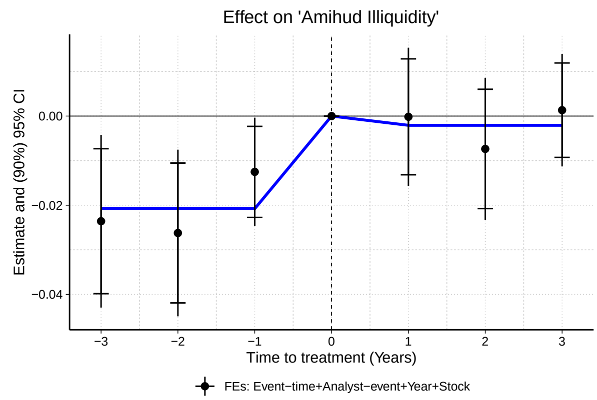
(b) Log number of shares in buy-side firm's portfolio



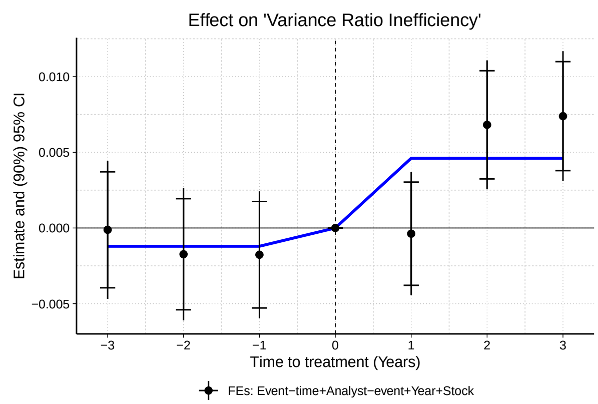
Notes: This figure shows the dynamic effects of analyst transitions from the sell-side to the buy-side on buy-side firm portfolio holdings at the quarterly frequency. The coefficients are estimated from a regression of buy-side portfolio holdings on time dummies relative to the analyst transition from I/B/E/S to the buy-side firm, interacted with indicators for treated stocks (covered by analysts who join the buy-side) vs control stocks (covered by analysts who remain on the sell-side). Each regression includes fixed effects at the year-by-quarter, stock, buy-side firm, and analyst-by-turnover event level, as indicated. The blue lines indicate pre- and post-average coefficient estimates. Figure 2a uses a dummy indicating if the stock is in the buy-side portfolio or not, Figure 2b uses the log-number of shares held by the buy-side firm as the dependent variable.

Figure 3: Sell-side I/B/E/S-exits (any destination) and market efficiency

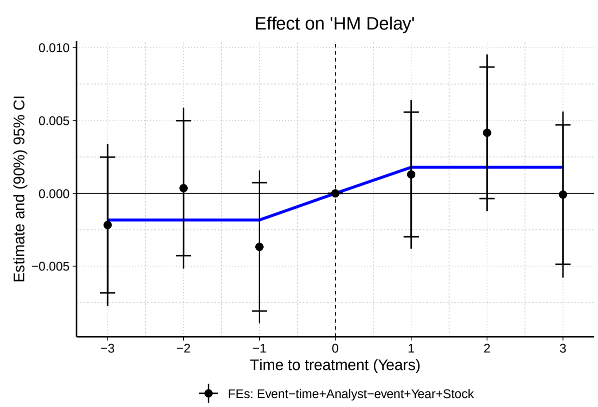
(a) Amihud Illiquidity



(b) Variance Ratio Inefficiency



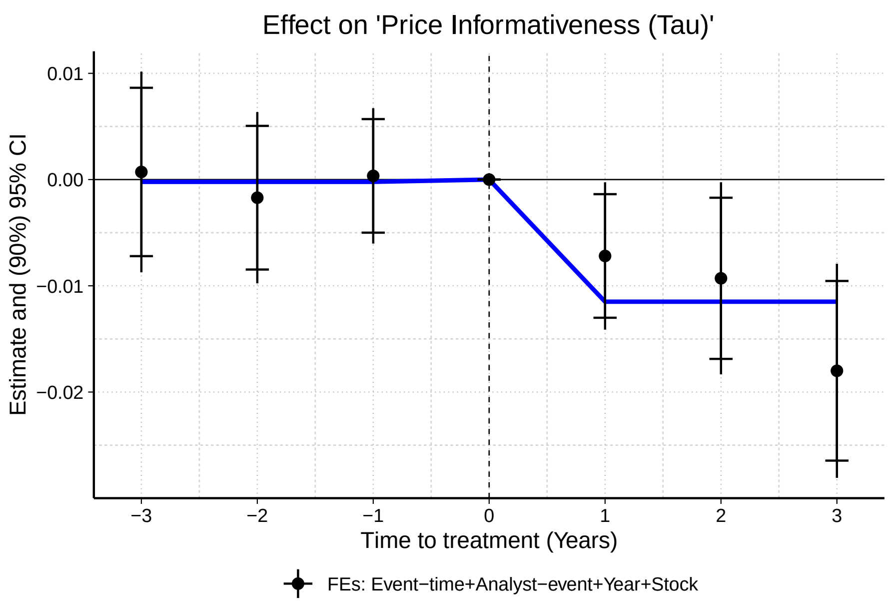
(c) Hou-Moskowitz Delay



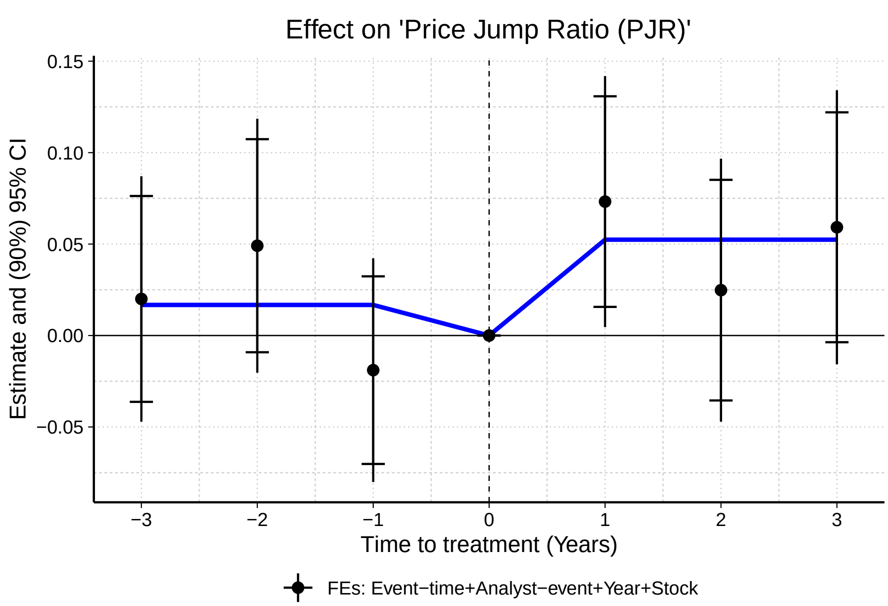
Notes: This figure shows the dynamic effects of analyst exits from I/B/E/S on three measures of stock price efficiency at the annual frequency: Amihud illiquidity (Fig. 3a), Variance Ratio inefficiency (Fig. 3b), and Hou and Moskowitz (2005) price delay (Fig. 3c). The coefficients are estimated from a regression of stock characteristics on time dummies relative to the analyst exit from I/B/E/S, interacted with indicators for treated stocks (covered by analysts who exit I/B/E/S) vs control stocks (covered by analysts who remain on the sell-side). Each regression includes fixed effects at the event-time, stock, year, and analyst-by-turnover event level. The blue lines indicate pre- and post-average coefficient estimates.

Figure 4: Sell-side I/B/E/S-exits to industry and price informativeness

(a) τ_π



(b) Price Jump Ratio (PJR)



Notes: This figure shows the dynamic effects of analyst exits from I/B/E/S on two measures of stock price informativeness at the annual frequency: future earnings to price sensitivity (Dávila and Parlatore, 2021) (Fig. 4a), and the Price-Jump-Ratio (Weller, 2018) (Fig. 4b). The sample includes only treated analysts who joined an industry- or non-finance position after exiting I/B/E/S. The coefficients are estimated from a regression of stock characteristics on time dummies relative to the analyst exit from I/B/E/S, interacted with indicators for treated stocks (covered by analysts who exit I/B/E/S) vs control stocks (covered by analysts who remain on the sell-side). Each regression includes fixed effects at the event-time, stock, year, and analyst-by-turnover event level. The blue lines indicate pre- and post-average coefficient estimates.

Table 1: Summary Statistics

Notes: This table reports descriptive statistics for the main variables used in the analysis. Panel 1a summarizes characteristics of analyst-year observations from I/B/E/S, including turnover outcomes, forecasting performance, and brokerage affiliation. Panel 1b presents summary statistics for institutional portfolio holdings matched to analyst exits, including portfolio composition, ownership shares, and performance. Panel 1c reports firm-year level measures used to assess price efficiency and the information environment, including illiquidity, return autocorrelation, forecast dispersion, and earnings surprises. Details on the sample construction and variable definitions are provided in Section 2 and Appendix Appendix A.

(a) Analyst-Year Panel

Variable	N	Mean	SD	P25	Median	P75
1(Exit Ibes)	34034	0.136	0.343	0.000	0.000	0.000
1(Buyside)	34034	0.017	0.131	0.000	0.000	0.000
1(Sellside)	34034	0.024	0.153	0.000	0.000	0.000
Accuracy Score	34034	50.999	19.636	41.361	52.077	61.673
Optimism Score	33583	49.272	19.035	39.669	49.360	59.074
Boldness Score	33593	48.817	19.624	37.398	47.395	59.016
Coverage Breadth	34034	11.151	8.645	3.000	10.000	17.000
Firms Covered	34034	16.978	8.941	11.000	16.000	21.500
Broker Size	34034	66.562	66.852	17.000	40.000	103.000
1(Top 10 Broker)	34034	0.282	0.450	0.000	0.000	1.000
Seniority (Years)	34034	7.482	6.355	2.000	6.000	11.000
1(Star)	34034	0.040	0.195	0.000	0.000	0.000
1(Affiliated)	34034	0.018	0.132	0.000	0.000	0.000

(b) Buyside-PF Year-Quarter Panel

Variable	N	Mean	SD	P5	P25	P50	P75	P95
1(Stock in Buyside PF)	203677	0.13	0.33	0.00	0.00	0.00	0.00	1.00
Unique Stocks Held	140999	478.41	739.01	14.00	55.00	144.00	497.00	2311.00
# Shares Held (Thsd)	203677	50.95	188.93	0.00	0.00	0.00	0.00	456.92
% in Buyside-PF (bps)	203677	0.03	0.17	0.00	0.00	0.00	0.00	0.11
% Float Held (x100)	203677	0.02	0.07	0.00	0.00	0.00	0.00	0.27
$ Value Held (/1000)	203677	951.79	3194.90	0.00	0.00	0.00	0.00	13218.67
AUM (B. USD)	140999	28.63	96.89	0.10	0.40	1.48	11.34	117.13
Return (Qtrly)	140860	0.03	0.10	-0.15	-0.01	0.04	0.08	0.18
Abn. Return (Qtrly)	99496	-0.01	0.04	-0.08	-0.02	0.00	0.01	0.06

... continued

(c) Stock-Year Panel

Variable	N	Mean	SD	P5	P25	P50	P75	P95
Illiquidity (x1000)	636790	50.05	540.61	0.03	0.12	0.49	2.95	78.82
VR Inefficiency	636700	0.16	0.16	0.01	0.06	0.12	0.22	0.42
HM-Delay	633499	0.25	0.24	0.02	0.08	0.17	0.34	0.80
Tau (Pi)	446857	0.30	0.27	0.00	0.06	0.23	0.50	0.81
PJR	281288	0.39	1.39	-2.08	-0.07	0.37	0.84	2.98
Analyst Coverage	690188	12.66	8.36	2.00	6.00	11.00	18.00	29.00
EPS Forecast SD	663440	0.09	0.15	0.01	0.02	0.04	0.09	0.34
Abs(SUE Score)	612946	2.16	2.85	0.10	0.51	1.18	2.54	8.03

Table 2: Analyst characteristics and I/B/E/S exits

Notes: This table reports linear probability models estimating the likelihood that an analyst exits I/B/E/S in a given year as a function of forecast accuracy and other analyst characteristics. The dependent variable is an indicator equal to one if the analyst exits I/B/E/S in the following year. Columns (1) and (2) include percentile-based indicators for forecast accuracy; column (3) uses a continuous accuracy score. Details on the sample construction and variable definitions are provided in Section 2 and Appendix Appendix A. All regressions include year, analyst SIC2, and brokerage fixed effects. Standard errors are clustered at the brokerage level. Coefficient estimates are reported with standard errors in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	1(Exit IBES)		
	(1)	(2)	(3)
1(Bottom 10%)	-0.0034		
	(0.0089)		
1(10-25%)	0.0027		
	(0.0064)		
1(25-40%)	0.0008		
	(0.0056)		
1(60-75%)	-0.0107*		
	(0.0064)		
1(75-90%)	-0.0213***		
	(0.0059)		
1(Top 10%)	-0.0307***		
	(0.0077)		
1(0-20%)		0.0001	
		(0.0064)	
1(20-40%)		0.0014	
		(0.0057)	
1(60-80%)		-0.0139**	
		(0.0054)	
1(80-100%)		-0.0245***	
		(0.0054)	
Accuracy Score (x10)			-0.0066***
			(0.0010)
1(Affiliated)	-0.0106	-0.0104	-0.0104
	(0.0123)	(0.0123)	(0.0123)
1(Star)	-0.0251**	-0.0249**	-0.0245**
	(0.0099)	(0.0100)	(0.0100)
Seniority	-0.0011***	-0.0011***	-0.0011***
	(0.0004)	(0.0004)	(0.0004)
1(Top 10 Broker)	-0.0058	-0.0060	-0.0060
	(0.0167)	(0.0167)	(0.0167)
Broker Size	0.0003*	0.0003*	0.0003*
	(0.0001)	(0.0001)	(0.0001)
Coverage	-0.0011***	-0.0011***	-0.0011***
	(0.0003)	(0.0003)	(0.0003)
Breadth	-0.0054***	-0.0054***	-0.0052***
	(0.0004)	(0.0004)	(0.0004)
Observations	34,034	34,034	34,034
R^2	0.0768	0.0767	0.0772
Within R^2	0.0170	0.0169	0.0175
Year FE	✓	✓	✓
Analyst SIC2 FE	✓	✓	✓
Brokerage FE	✓	✓	✓
SE Cluster	Brokerage	Brokerage	Brokerage

Table 3: Analyst characteristics and job transitions

Notes: This table reports linear probability models estimating the relationship between analyst forecast accuracy (percentile indicators) and the likelihood of transitioning to specific employment destinations after exiting I/B/E/S. Panel 3a presents results for mutually exclusive categories of post-exit employment: buyside (e.g., hedge funds, asset managers), sell-side (other brokerages), corporate roles, and other occupations. Panel 3b splits buyside transitions into large vs. small employers. Panel 3c further distinguishes buyside destinations into mutual funds / pension funds / asset managers (MF/PF/AM), alternative investors (hedge funds (HF), private equity (PE), venture capital (VC)), and private banking/wealth management (PB/WM). Details on the sample construction and variable definitions are provided in Section 2 and Appendix Appendix A. All regressions include year, analyst SIC2, and brokerage fixed effects. Standard errors are clustered at the brokerage level. Coefficient estimates are reported with standard errors in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

(a) By destination

	1(Buyside)	1(Sellside)	1(Corporate)	1(Other)
	(1)	(2)	(3)	(4)
1(Bottom 10%)	-0.0061**	-0.0004	-0.0009	0.0049*
	(0.0027)	(0.0039)	(0.0074)	(0.0026)
1(10-25%)	-0.0027	0.0012	-0.0054	0.0084***
	(0.0023)	(0.0028)	(0.0050)	(0.0023)
1(25-40%)	0.0025	0.0011	-0.0026	0.0031*
	(0.0019)	(0.0028)	(0.0041)	(0.0017)
1(60-75%)	0.0051*	-0.0035	-0.0075	-0.0033**
	(0.0027)	(0.0031)	(0.0058)	(0.0017)
1(75-90%)	0.0011	-0.0050**	-0.0037	-0.0026
	(0.0024)	(0.0025)	(0.0047)	(0.0017)
1(Top 10%)	0.0012	-0.0095***	-0.0026	-0.0019
	(0.0032)	(0.0035)	(0.0060)	(0.0022)
Observations	34,034	34,034	34,034	34,034
R^2	0.0252	0.0347	0.0687	0.0395
Within R^2	0.0029	0.0038	0.0014	0.0021
Analyst Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Analyst SIC2 FE	✓	✓	✓	✓
Brokerage FE	✓	✓	✓	✓
SE Cluster	Brokerage	Brokerage	Brokerage	Brokerage

... continued

(b) Large vs small buy-side institutions

	1(Large Buyside)	1(Small Buyside)	1(Large Buyside)	1(Small Buyside)
	(1)	(2)	(3)	(4)
1(Bottom 10%)	-0.0019	-0.0042*		
	(0.0013)	(0.0024)		
1(10-25%)	-0.0017*	-0.0010		
	(0.0010)	(0.0023)		
1(25-40%)	0.0003	0.0022		
	(0.0011)	(0.0018)		
1(60-75%)	0.0009	0.0042**		
	(0.0011)	(0.0021)		
1(75-90%)	0.0048***	-0.0036*		
	(0.0013)	(0.0020)		
1(Top 10%)	0.0066***	-0.0054**		
	(0.0018)	(0.0024)		
1(0-20%)			-0.0019	-0.0020
			(0.0012)	(0.0021)
1(20-40%)			-0.0002	0.0009
			(0.0010)	(0.0017)
1(60-80%)			0.0017	0.0022
			(0.0011)	(0.0018)
1(80-100%)			0.0057***	-0.0044**
			(0.0013)	(0.0021)
Observations	34,034	34,034	34,034	34,034
R^2	0.0212	0.0234	0.0210	0.0231
Within R^2	0.0022	0.0023	0.0021	0.0020
Analyst Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Analyst SIC2 FE	✓	✓	✓	✓
Brokerage FE	✓	✓	✓	✓
SE Cluster	Brokerage	Brokerage	Brokerage	Brokerage

... continued

(c) Types of buy-side institutions

	1(MF / PF / AM)	1(HF / PE / VC)	1(PB / WM)
	(1)	(2)	(3)
1(Bottom 10%)	-0.0017	-0.0048**	0.0011
	(0.0012)	(0.0021)	(0.0013)
1(10-25%)	-0.0014	-0.0034*	0.0026**
	(0.0010)	(0.0020)	(0.0012)
1(25-40%)	0.0001	0.0002	0.0016
	(0.0011)	(0.0018)	(0.0010)
1(60-75%)	0.0012	0.0002	0.0039***
	(0.0011)	(0.0018)	(0.0011)
1(75-90%)	0.0045***	-0.0038*	0.0006
	(0.0013)	(0.0019)	(0.0009)
1(Top 10%)	0.0063***	-0.0058***	0.0002
	(0.0018)	(0.0022)	(0.0010)
Observations	34,034	34,034	34,034
R^2	0.0192	0.0194	0.0251
Within R^2	0.0022	0.0021	0.0008
Analyst Controls	✓	✓	✓
Year FE	✓	✓	✓
Analyst SIC2 FE	✓	✓	✓
Brokerage FE	✓	✓	✓
SE Cluster	Brokerage	Brokerage	Brokerage

Table 4: Pre-turnover analyst coverage and moves to the buyside

Notes: This table summarizes cross-sectional linear probability models, examining whether buyside firms are more likely to hire analysts who previously covered their portfolio stocks. The dependent variable is an indicator equal to one if an analyst transitions to a buyside firm in a given quarter. The key independent variable is a dummy for whether the analyst covered any stock held by the hiring buyside firm ("In Buyside PF") prior to the transition. The estimates are obtained from comparing analysts who leave for a buy-side firm and matched control analysts who stay on the sell-side in the year before the respective analyst-transition. Analyst controls are similar to the previous tables. Column (1) includes fixed effects for year-quarter and analyst industry (SIC2). Column (2) adds buyside firm fixed effects. Standard errors are clustered at the analyst level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	1(Analyst moves to Buyside)	
	(1)	(2)
1(In Buyside PF)	0.0805**	0.2263***
	(0.0395)	(0.0695)
Accuracy Score	0.0005	-0.0002
	(0.0012)	(0.0015)
Optimism Score	0.0003	0.0021
	(0.0010)	(0.0013)
Boldness Score	0.0018	0.0018
	(0.0012)	(0.0015)
1(Top 10 Broker)	0.0851**	0.1413***
	(0.0371)	(0.0544)
Coverage	-0.0003	-0.0011
	(0.0025)	(0.0032)
Breadth	-0.0061***	-0.0072**
	(0.0020)	(0.0029)
Observations	965	965
R^2	0.0937	0.2179
Within R^2	0.0265	0.0450
Analyst SIC2 FE	✓	✓
Year-Qtr FE	✓	✓
Buyside Firm FE		✓
SE Cluster	Analyst	Analyst

Table 5: Moves to the buy-side and buy-side portfolio holdings

Notes: This table examines whether buyside institutions increase their holdings in stocks previously covered by analysts they hire, using difference-in-differences regressions at the stock-year-quarter level as specified in Equation (3). The dependent variable in Panel 5a is an indicator equal to one if a given stock is held by the hiring buyside firm. In Panel 5b, the dependent variable is the log of one plus the number of shares held. The main variable of interest is the interaction between '1(Treated)'—an indicator for stocks previously covered by analysts who leave the sell-side for the hiring buyside firm—and '1(Post)', which equals one in quarters after the treated analyst's transition. Regressions include fixed effects at the event-time, stock, buyside firm, and analyst-by-event levels as indicated. Standard errors are double clustered by analyst and buyside firm ("Analy+Mgr"). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

(a) Is the stock in the buyside firm's PF?

	1(Stock is in Buyside PF)				
	(1)	(2)	(3)	(4)	(5)
1(Treated)	0.0254**	0.0254**	0.0205**	0.0094	
	(0.0114)	(0.0114)	(0.0095)	(0.0066)	
1(Post)	0.0029				
	(0.0060)				
1(Treated) × 1(Post)	0.0193**	0.0193**	0.0189**	0.0189**	0.0189**
	(0.0083)	(0.0083)	(0.0085)	(0.0085)	(0.0085)
Constant	0.1165***				
	(0.0256)				
Observations	203,677	203,677	202,266	202,266	202,266
R^2	0.0026	0.0031	0.2365	0.4845	0.5150
Within R^2		0.0025	0.0017	0.0011	0.0003
Event-time FE		✓	✓	✓	✓
Stock FE			✓	✓	✓
Buyside Firm FE				✓	✓
Analyst-by-event FE					✓
SE Cluster	Analy+Mgr	Analy+Mgr	Analy+Mgr	Analy+Mgr	Analy+Mgr

... continued

(b) Log # of Shares in Buyside PF

	Log(1+# Shares Held)				
	(1)	(2)	(3)	(4)	(5)
1(Treated)	0.3232**	0.3232**	0.2759**	0.1368*	
	(0.1394)	(0.1394)	(0.1171)	(0.0777)	
1(Post)	0.0239				
	(0.0688)				
1(Treated) × 1(Post)	0.2418**	0.2418**	0.2356**	0.2356**	0.2356**
	(0.1000)	(0.1000)	(0.1024)	(0.1024)	(0.1024)
Constant	1.379***				
	(0.3100)				
Observations	203,677	203,677	202,266	202,266	202,266
R^2	0.0029	0.0033	0.2441	0.4961	0.5275
Within R^2		0.0027	0.0020	0.0013	0.0004
Event-time FE		✓	✓	✓	✓
Stock FE			✓	✓	✓
Buyside Firm FE				✓	✓
Analyst-by-event FE					✓
SE Cluster	Analy+Mgr	Analy+Mgr	Analy+Mgr	Analy+Mgr	Analy+Mgr

Table 6: Heterogeneity in the effect on buy-side portfolios

Notes: This table examines heterogeneity in the effect of analyst transitions to the buyside on portfolio holdings. Each panel estimates a stacked difference-in-differences specification at the stock–year–quarter level, following Equation (3). The dependent variable in all columns is an indicator equal to one if the stock is held by the hiring buyside firm. Panel 6a splits the sample based on analyst characteristics—accuracy, optimism, and boldness—measured prior to turnover. Panel 6b splits the sample by pre-turnover analyst coverage, the magnitude of absolute standardized unexpected earnings (Abs(SUE)), and the concentration of business segments (HHI). Panel 6c examines splits by the hiring buyside firm's performance and assets under management (AUM) in the year before the analyst joins. All regressions include fixed effects at the event-time, stock, buyside firm, and analyst-by-event level, as indicated. Standard errors are double clustered by analyst-event and buyside firm ("A+M"). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

(a) Analyst characteristics

	1(In Buyside PF)					
Split:	Accuracy		Optimism		Boldness	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
1(Treated) × 1(Post)	-0.0054	0.0454***	-0.0005	0.0318**	0.0290***	0.0106
	(0.0110)	(0.0170)	(0.0096)	(0.0140)	(0.0103)	(0.0129)
Observations	101,184	100,844	101,099	100,929	101,252	100,776
R^2	0.5264	0.5725	0.5529	0.5512	0.5538	0.5563
Within R^2	0.00003	0.0022	0.0000003	0.0011	0.0008	0.0001
Event-time FE	✓	✓	✓	✓	✓	✓
Stock FE	✓	✓	✓	✓	✓	✓
Buyside Firm FE	✓	✓	✓	✓	✓	✓
Analyst-by-event FE	✓	✓	✓	✓	✓	✓
SE Cluster	A+M	A+M	A+M	A+M	A+M	A+M

... continued

(b) Information environment characteristics

	1(In Buyside PF)					
Split:	Analyst Coverage		Abs(SUE)		HHI Segments	
	No	Yes	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
1(Treated) × 1(Post)	0.0343***	0.0078	0.0188	0.0253***	0.0243**	0.0092
	(0.0131)	(0.0087)	(0.0115)	(0.0085)	(0.0094)	(0.0149)
Observations	98,294	82,722	90,457	90,423	132,022	39,151
R^2	0.5688	0.5685	0.5789	0.5535	0.5428	0.6187
Within R^2	0.0014	0.00005	0.0003	0.0008	0.0006	0.0001
Event-time FE	✓	✓	✓	✓	✓	✓
Stock FE	✓	✓	✓	✓	✓	✓
Buyside Firm FE	✓	✓	✓	✓	✓	✓
Analyst-by-event FE	✓	✓	✓	✓	✓	✓
SE Cluster	A+M	A+M	A+M	A+M	A+M	A+M

(c) Buy-side characteristics

	1(In Buyside PF)							
Split:	Ret (Year before move)				AUM (Year before move)			
	Low		High		Low		High	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1(Treated)	0.0226		0.0367*		0.0180		0.0260	
	(0.0240)		(0.0188)		(0.0114)		(0.0258)	
1(Post)	-0.0104		-0.0064		0.0117		-0.0298	
	(0.0220)		(0.0085)		(0.0077)		(0.0232)	
1(Treated) × 1(Post)	0.0397*	0.0398*	0.0192*	0.0185	0.0334**	0.0321**	0.0276	0.0281
	(0.0221)	(0.0229)	(0.0110)	(0.0112)	(0.0150)	(0.0154)	(0.0200)	(0.0208)
Constant	0.1710***		0.1577***		0.0482***		0.2878***	
	(0.0406)		(0.0377)		(0.0087)		(0.0574)	
Observations	72,403	71,893	69,683	69,173	71,757	71,417	70,329	69,649
R^2	0.0031	0.5773	0.0035	0.5664	0.0071	0.3820	0.0025	0.5856
Within R^2		0.0013		0.0003		0.0014		0.0005
Event-time FE		✓		✓		✓		✓
Stock FE		✓		✓		✓		✓
Buyside Firm FE		✓		✓		✓		✓
Analyst-by-event FE		✓		✓		✓		✓
SE Cluster	A+M	A+M	A+M	A+M	A+M	A+M	A+M	A+M

Table 7: Sell-side to buy-side transitions and buy-side performance

Notes: This table examines how analyst transitions from the sell-side to the buy-side affect the hiring firm's performance and size. The regressions estimate a stacked difference-in-differences specification at the analyst-by-year-quarter level. The key independent variable is the interaction between '1(Treated)'—an indicator for analysts who move to a given buy-side firm from I/B/E/S—and '1(Post)', which takes the value one in the quarters after the analyst joins. The dependent variables are: the hiring buyside firm's quarterly portfolio return (columns 1–2), abnormal quarterly return relative to a Fama-French 3-factor model (columns 3–4), and the log of assets under management (AUM) (AUM are first scaled by 1,000 for legibility) (columns 5–6). Columns (2), (4), and (6) include fixed effects at the event-time, buyside firm, and analyst-by-event level, as indicated. Standard errors are clustered by analyst-event and buyside firm ("Analy+Mgr"). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Buyside Return		Abnormal Return		log AUM (x1000)	
	(1)	(2)	(3)	(4)	(5)	(6)
1(Treated)	-0.0016		0.0015**		0.0820	
	(0.0013)		(0.0007)		(0.1169)	
1(Post)	-0.0128***		0.0010		-0.0911	
	(0.0039)		(0.0019)		(0.0993)	
1(Treated) × 1(Post)	-0.0002	0.0004	-0.0001	-0.0007	-0.1049*	-0.0320
	(0.0021)	(0.0021)	(0.0010)	(0.0009)	(0.0560)	(0.0447)
Constant	0.0406***		-0.0085***		14.71***	
	(0.0029)		(0.0017)		(0.2771)	
Observations	12,050	12,050	8,579	8,579	12,050	12,050
R^2	0.0045	0.0893	0.0004	0.1602	0.0009	0.9379
Within R^2		0.0000008		0.00002		0.0002
Event-time FE		✓		✓		✓
Buyside Firm FE		✓		✓		✓
Analyst-by-event FE		✓		✓		✓
SE Cluster	Analy+Mgr	Analy+Mgr	Analy+Mgr	Analy+Mgr	Analy+Mgr	Analy+Mgr

Table 8: Analyst I/B/E/S exits and price efficiency

Notes: This table examines how the exit of analysts from I/B/E/S affects stock-level price efficiency. The analysis is based on stacked difference-in-differences regressions estimated at the stock-year level. The key independent variable is the interaction between '1(Treated)', which indicates stocks covered by an analyst who leaves I/B/E/S, and '1(Post)', which equals one in years after the analyst's exit. Panel 8a presents results for the full sample of analyst exits, using five measures of price efficiency: Amihud illiquidity, variance ratio (VR) inefficiency, Hou–Moskowitz price delay, earnings-to-price sensitivity (τ_π) from Dávila and Parlatore (2021), and the Price Jump Ratio (PJR) from Weller (2018). Panel 8b shows heterogeneity by destination, comparing exits to other sell-side firms, buyside institutions, and industry roles. All regressions include event-time, stock, year, and analyst-by-event fixed effects. Standard errors are clustered at the analyst-by-event level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

(a) Full sample of all analyst exits from I/B/E/S

	Illiquidity	VR Inefficiency	Delay	τ_π	PJR
	(1)	(2)	(3)	(4)	(5)
1(Treated) × 1(Post)	0.0137***	0.0055***	0.0036*	-0.0051**	0.0193*
	(0.0047)	(0.0012)	(0.0018)	(0.0024)	(0.0116)
Observations	488,058	487,971	485,003	329,917	224,641
R^2	0.4343	0.2308	0.4084	0.5575	0.1294
Within R^2	0.00004	0.00006	0.00002	0.00004	0.000010
Event-time FE	✓	✓	✓	✓	✓
Analyst-by-event FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Stock FE	✓	✓	✓	✓	✓
SE Cluster	Analyst-by-Event	Analyst-by-Event	Analyst-by-Event	Analyst-by-Event	Analyst-by-Event

(b) Heterogeneity by analyst destination

	Exit to Sellside		Exit to Buyside		Exit to Industry	
	τ_π	PJR	τ_π	PJR	τ_π	PJR
	(1)	(2)	(3)	(4)	(5)	(6)
1(Treated) × 1(Post)	-0.0017	-0.0015	-0.0021	0.0233	-0.0110**	0.0404**
	(0.0039)	(0.0195)	(0.0045)	(0.0227)	(0.0043)	(0.0194)
Observations	274,056	183,307	264,137	177,302	273,315	183,909
R^2	0.5543	0.1293	0.5562	0.1281	0.5548	0.1287
Within R^2	0.000002	0.00000003	0.000003	0.000006	0.00009	0.00002
Event-time FE	✓	✓	✓	✓	✓	✓
Analyst-by-event FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Stock FE	✓	✓	✓	✓	✓	✓
SE Cluster	Analyst-by-Event	Analyst-by-Event	Analyst-by-Event	Analyst-by-Event	Analyst-by-Event	Analyst-by-Event

Table 9: Heterogeneous effects of IBES exit on price efficiency

Notes: This table investigates heterogeneity in the effect of I/B/E/S exits on price efficiency based on firm and coverage characteristics. Analogous to Table 8, we estimate difference-in-differences regressions at the stock-year level, focusing on the interaction term 1(Treated) × 1(Post), where 1(Treated) indicates stocks covered by an analyst who exits I/B/E/S, and 1(Post) is an indicator for the post-exit period. Panel 9a splits the sample by pre-exit analyst coverage (number of I/B/E/S estimates), Panel 9b by the absolute value of standardized unexpected earnings (Abs(SUE)), and Panel 9c by the Herfindahl-Hirschman Index (HHI) of segment sales, a proxy for firm complexity. In each case, treated analysts are split along the respective dimension, while all control observations are retained in the regression. The dependent variables include Amihud illiquidity, variance ratio (VR) inefficiency, and price delay, as in Table 8. All regressions include event-time, year, stock, and analyst-by-event fixed effects. Standard errors are clustered at the analyst-by-event level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

(a) Effect by analyst coverage

	Analyst Coverage (before exit): Low			Analyst Coverage (before exit): High		
	Illiquidity	VR Ineff.	Delay	Illiquidity	VR Ineff.	Delay
	(1)	(2)	(3)	(4)	(5)	(6)
1(Treated) × 1(Post)	0.0239***	0.0110***	0.0097***	-0.0044***	0.0048**	0.0039
	(0.0081)	(0.0020)	(0.0029)	(0.0011)	(0.0019)	(0.0029)
Observations	857,571	857,469	854,182	869,080	868,995	865,825
R^2	0.4266	0.2348	0.4156	0.4278	0.2347	0.4173
Within R^2	0.0001	0.0002	0.00008	0.000005	0.00004	0.00001
Event-time FE	✓	✓	✓	✓	✓	✓
Analyst-by-event FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Stock FE	✓	✓	✓	✓	✓	✓
SE Cluster	Analyst	Analyst	Analyst	Analyst	Analyst	Analyst

... continued

(b) Complex firms: effect by abs(SUE)

	Abs(SUE) Low			Abs(SUE) High		
	Illiquidity	VR Ineff.	Delay	Illiquidity	VR Ineff.	Delay
	(1)	(2)	(3)	(4)	(5)	(6)
1(Treated) × 1(Post)	-0.0022	0.0007	-0.0007	0.0228***	0.0138***	0.0033
	(0.0022)	(0.0019)	(0.0030)	(0.0078)	(0.0019)	(0.0029)
Observations	873,147	873,054	869,761	865,960	865,838	862,201
R^2	0.4256	0.2359	0.4163	0.4261	0.2337	0.4164
Within R^2	0.000001	0.0000008	0.0000005	0.0001	0.0003	0.000009
Event-time FE	✓	✓	✓	✓	✓	✓
Analyst-by-event FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Stock FE	✓	✓	✓	✓	✓	✓
SE Cluster	Analyst	Analyst	Analyst	Analyst	Analyst	Analyst

(c) Complex firms: HHI of sales across business segments

	HHI (Segment Sales) Low			HHI (Segment Sales) High		
	Illiquidity	VR Ineff.	Delay	Illiquidity	VR Ineff.	Delay
	(1)	(2)	(3)	(4)	(5)	(6)
1(Treated) × 1(Post)	0.0035	0.0029	-0.0033	0.0247***	0.0120***	0.0030
	(0.0030)	(0.0019)	(0.0029)	(0.0085)	(0.0019)	(0.0030)
Observations	860,525	860,436	857,195	858,602	858,475	854,820
R^2	0.4273	0.2372	0.4177	0.4288	0.2348	0.4151
Within R^2	0.000003	0.00001	0.000010	0.0001	0.0002	0.000007
Event-time FE	✓	✓	✓	✓	✓	✓
Analyst-by-event FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Stock FE	✓	✓	✓	✓	✓	✓
SE Cluster	Analyst	Analyst	Analyst	Analyst	Analyst	Analyst

Table 10: I/B/E/S exits — effect on information environment

Notes: This table examines how analyst exits from I/B/E/S affect the firm-level information environment. We estimate difference-in-differences regressions at the stock-year level, focusing on the interaction term 1(Treated) × 1(Post), where 1(Treated) indicates stocks covered by an analyst who exits I/B/E/S, and 1(Post) is an indicator for the post-exit period. The dependent variables are the absolute value of standardized unexpected earnings (Abs(SUE)) in column (1), the standard deviation of analyst EPS forecasts for a given stock in column (2), and the number of analyst estimates per stock-year in column (3). All regressions include event-time, year, stock, and analyst-by-event fixed effects. Standard errors are clustered at the analyst-by-event level ("Analy."). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Abs(SUE)	EPS Forecast SD	Coverage
	(1)	(2)	(3)
1(Treated) × 1(Post)	0.0336**	0.0042***	-0.4539***
	(0.0154)	(0.0011)	(0.0470)
Observations	612,946	663,440	690,188
R^2	0.1761	0.5336	0.8482
Event-time FE	✓	✓	✓
Analyst-by-event FE	✓	✓	✓
Year FE	✓	✓	✓
Stock FE	✓	✓	✓
SE Cluster	Analy.	Analy.	Analy.

Appendix A Variable Definitions

- *Accuracy* is the average value of relative *Accuracy Rank* for all firms followed by analyst i in year t. Similar to Hong et al. (2000), we scale it between 0 and 100. The *Accuracy Rank* is given by

$$Accuracy\ Rank = 100 - (\frac{Forecast\ Error\ Rank}{Number\ of\ Analysts\ Following - 1}) \times 100,$$

  where *Forecast Error* is the absolute difference between the forecast and actual earning.

- *Affiliated Analyst* is a dummy variable that equals one if the analyst's investment bank was the lead underwriter of an initial public offering (IPO) in the past five years, and zero otherwise.

- *All-Star* is a dummy variable equals one if the analyst is named to *Institutional Investor*'s All-American team during the past five years, and zero otherwise.

- *Analysts Following* is the number of analysts who follow this stock in a given year.

- *Breadth-Firm* is the number of stocks covered by the analyst in a given year.

- *Avg. Coverage* is the average analyst coverage (i.e., the number of analyst covering a firm) of firms covered by the analyst in a given year.

- *Broker Size* is a dummy variable that is equal to one if broker is among the largest 10 brokers by the number of analysts in a given year.

- *Boldness* is the average value of relative *Boldness Rank* for all firms followed by analyst i in year t. Following Hong et al. (2000), we scale it between 0 and 100. The *Boldness Rank* is calculated as

$$Boldness\ Rank = 100 - (\frac{Forecast\ Boldness\ Rank}{Number\ of\ Analysts\ Following - 1}) \times 100,$$

  where *Forecast Boldness* is the absolute difference between forecast of analyst i and the average of forecasts by all analysts other than i.

- *Buy-side Experience* is a dummy variable that is equal to one if the analyst has previously worked at buy-side.

- *Corporate Experience* is a dummy variable that is equal to one if the analyst has a previous corporate working (non-investment banking) experience.

- *Institutional Ownership* is the average of stock ownership held by institutional investors for all firms followed by analyst i in year t.

- *Optimism* is the average value of *Optimism Dummy* for all firms followed by analyst i in year t. *Optimism Dummy* is defined as one if earning forecast is higher than actual earning, and zero otherwise.

- *Postgraduate* is a dummy variable that is equal to one if the analyst indicates that he or she has a master(non-MBA) or Ph.D degrees on LinkedIn profile, and zero otherwise.
- *Seniority* is the number of years an analyst has been in the IBES database.
- *Specialty Major* is a dummy variable that is equal to one if the analyst has an educational degree specializing in the area related to the industry that she covers, and zero otherwise. For instance, if an analyst has undergraduate or post-graduate degree in computer science, and she also covers stocks in the relevant sector such as technology.

Appendix B Additional robustness tests

Table B1: Analyst characteristics and job transitions — Robustness

Notes: This table presents robustness tests corresponding to Table 3 for the relationship between analyst characteristics and the likelihood of transitioning to different destinations outside of I/B/E/S. The outcome variables are indicator variables for the analyst's next employment category: buy-side, sell-side, corporate, or other destinations. Panel B1a implements an alternative bins of forecasting accuracy compared to the main model. Panel B1b uses a continuous specification of analyst accuracy. Panel B1c modifies the control group in each regression across columns (1) through (4) to include only analysts who do not exit I/B/E/S, respectively. Panel B1d distinguishes between types of sell-side destinations (research, non-research, and broader sell-side roles), while Panel B1e disaggregates industry destinations (e.g., finance, investor relations, and other non-finance roles). All regressions include controls for analyst characteristics, year fixed effects, 2-digit SIC fixed effects, and brokerage fixed effects. Standard errors are clustered by brokerage. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

(a) By destination – alternative specification

	1(Buyside)	1(Sellside)	1(Corporate)	1(Other)
	(1)	(2)	(3)	(4)
1(0-20%)	-0.0039*	0.0013	-0.0033	0.0067***
	(0.0023)	(0.0031)	(0.0053)	(0.0023)
1(20-40%)	0.0007	0.0006	-0.0020	0.0038**
	(0.0018)	(0.0024)	(0.0038)	(0.0017)
1(60-80%)	0.0039*	-0.0038	-0.0073	-0.0030*
	(0.0023)	(0.0027)	(0.0049)	(0.0016)
1(80-100%)	0.0013	-0.0068***	-0.0018	-0.0027
	(0.0024)	(0.0025)	(0.0047)	(0.0017)
Observations	34,034	34,034	34,034	34,034
R^2	0.0251	0.0346	0.0687	0.0393
Within R^2	0.0028	0.0038	0.0013	0.0020
Analyst Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Analyst SIC2 FE	✓	✓	✓	✓
Brokerage FE	✓	✓	✓	✓
SE Cluster	Brokerage	Brokerage	Brokerage	Brokerage

... continued

(b) By destination – continuous specification

	1(Buyside)	1(Sellside)	1(Corporate)	1(Other)
	(1)	(2)	(3)	(4)
Accuracy Score (x10)	0.0008*	-0.0017***	-0.0003	-0.0015***
	(0.0004)	(0.0005)	(0.0008)	(0.0004)
Observations	34,034	34,034	34,034	34,034
R^2	0.0249	0.0347	0.0686	0.0389
Within R^2	0.0025	0.0038	0.0012	0.0015
Analyst Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Analyst SIC2 FE	✓	✓	✓	✓
Brokerage FE	✓	✓	✓	✓
SE Cluster	Brokerage	Brokerage	Brokerage	Brokerage

... continued

(c) By destination – alternative control group

	1(Buyside)	1(Sellside)	1(Corporate)	1(Other)
	(1)	(2)	(3)	(4)
1(Bottom 10%)	-0.0072**	-0.0004	-0.0014	0.0059*
	(0.0030)	(0.0046)	(0.0087)	(0.0032)
1(10-25%)	-0.0032	0.0012	-0.0054	0.0097***
	(0.0026)	(0.0032)	(0.0056)	(0.0026)
1(25-40%)	0.0027	0.0012	-0.0026	0.0035*
	(0.0021)	(0.0031)	(0.0046)	(0.0019)
1(60-75%)	0.0051*	-0.0041	-0.0089	-0.0040**
	(0.0030)	(0.0034)	(0.0062)	(0.0019)
1(75-90%)	0.0007	-0.0059**	-0.0055	-0.0033*
	(0.0027)	(0.0028)	(0.0052)	(0.0019)
1(Top 10%)	0.0005	-0.0115***	-0.0055	-0.0027
	(0.0037)	(0.0039)	(0.0069)	(0.0024)
Observations	30,007	30,230	29,957	29,824
R^2	0.0310	0.0406	0.0769	0.0471
Within R^2	0.0038	0.0051	0.0025	0.0028
Analyst Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Analyst SIC2 FE	✓	✓	✓	✓
Brokerage FE	✓	✓	✓	✓
SE Cluster	Brokerage	Brokerage	Brokerage	Brokerage

... continued

(d) To sellside – type of sellside

	1(Sellside)	1(Sellside Research)	1(Sellside Other)	1(Sellside Broad)
	(1)	(2)	(3)	(4)
1(0-20%)	0.0013	0.0001	0.0012	0.0037**
	(0.0031)	(0.0026)	(0.0013)	(0.0019)
1(20-40%)	0.0006	0.0005	0.00009	0.0017
	(0.0024)	(0.0021)	(0.0012)	(0.0017)
1(60-80%)	-0.0038	-0.0040*	0.0002	-0.0004
	(0.0027)	(0.0023)	(0.0010)	(0.0016)
1(80-100%)	-0.0068***	-0.0071***	0.0003	-0.0020
	(0.0025)	(0.0022)	(0.0011)	(0.0015)
Observations	34,034	34,034	34,034	34,034
R^2	0.0346	0.0310	0.0349	0.0312
Within R^2	0.0038	0.0033	0.0006	0.0008
Analyst Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Analyst SIC2 FE	✓	✓	✓	✓
Brokerage FE	✓	✓	✓	✓
SE Cluster	Brokerage	Brokerage	Brokerage	Brokerage

... continued

(e) To industry – type of industry

	1(Industry)	1(Non-Sell Non-Buy)	1(Industry Finance)	1(Non-Finance)	1(Investor Relations)
	(1)	(2)	(3)	(4)	(5)
1(0-20%)	-0.0040*	0.0027	-0.0035**	-0.0023	-0.0025
	(0.0022)	(0.0033)	(0.0017)	(0.0037)	(0.0030)
1(20-40%)	-0.0019	0.0018	-0.0023	-0.0007	-0.0006
	(0.0021)	(0.0030)	(0.0014)	(0.0033)	(0.0033)
1(60-80%)	-0.0068***	-0.0098***	-0.0030*	0.0024	-0.0031
	(0.0022)	(0.0029)	(0.0015)	(0.0037)	(0.0030)
1(80-100%)	-0.0071***	-0.0099***	-0.0035*	0.0016	-0.0016
	(0.0022)	(0.0030)	(0.0019)	(0.0035)	(0.0028)
Observations	34,034	34,034	34,034	34,034	34,034
R^2	0.0228	0.0331	0.0230	0.0590	0.0545
Within R^2	0.0011	0.0021	0.0007	0.0005	0.0004
Analyst Controls	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Analyst SIC2 FE	✓	✓	✓	✓	✓
Brokerage FE	✓	✓	✓	✓	✓
SE Cluster	Brokerage	Brokerage	Brokerage	Brokerage	Brokerage

Table B2: Effect on portfolio holdings — robustness

Notes: This table presents robustness tests corresponding to Table 5 examining the impact of analyst transitions from the sell side to the buy side on subsequent portfolio holdings of the hiring buy-side firm. Panel B2a investigates whether the observed portfolio effects are driven by the treatment group (stocks previously covered by the hired analyst) or by changes among the control group (stocks not covered by the analyst). Columns (1) and (2) include only treated analysts, columns (3) and (4) include only matched control analysts. Instead of estimating an interaction effect of '1(Treated)' and '1(Post)', these regressions estimate only the unconditional effect of '1(Post)' in each subsample. Panel B2b tests alternative measures of buy-side holdings, including portfolio weights, percent of float held, and market value of positions. Panel B2c introduces buy-side firm-by-year-quarter fixed effects to better control for time-varying manager-level characteristics. Regressions include fixed effects for stock, event time, and analyst-by-event as indicated. Some specifications also include buy-side firm fixed effects or buy-side firm-by-year-quarter fixed effects, as noted. Standard errors are double clustered at the analyst-event ('Analy.') and buy-side firm ('Mgr') level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

(a) Effect from treated or control analysts?

	Treated		Control	
	1(In Buyside PF)	Log(1+# Shares)	1(In Buyside PF)	Log(1+# Shares)
	(1)	(2)	(3)	(4)
1(Post)	0.0473***	0.5031***	-0.0024	-0.0652
	(0.0159)	(0.1298)	(0.0308)	(0.3518)
Observations	57,851	57,851	144,415	144,415
R^2	0.5629	0.5744	0.5386	0.5535
Within R^2	0.00002	0.00002	0.0000002	0.0000009
Event-time FE	✓	✓	✓	✓
Stock FE	✓	✓	✓	✓
Buyside Firm FE	✓	✓	✓	✓
Analyst-by-event FE	✓	✓	✓	✓
SE Cluster	Analy+Mgr	Analy+Mgr	Analy+Mgr	Analy+Mgr

... continued

(b) Alternative measures of buy-side holdings

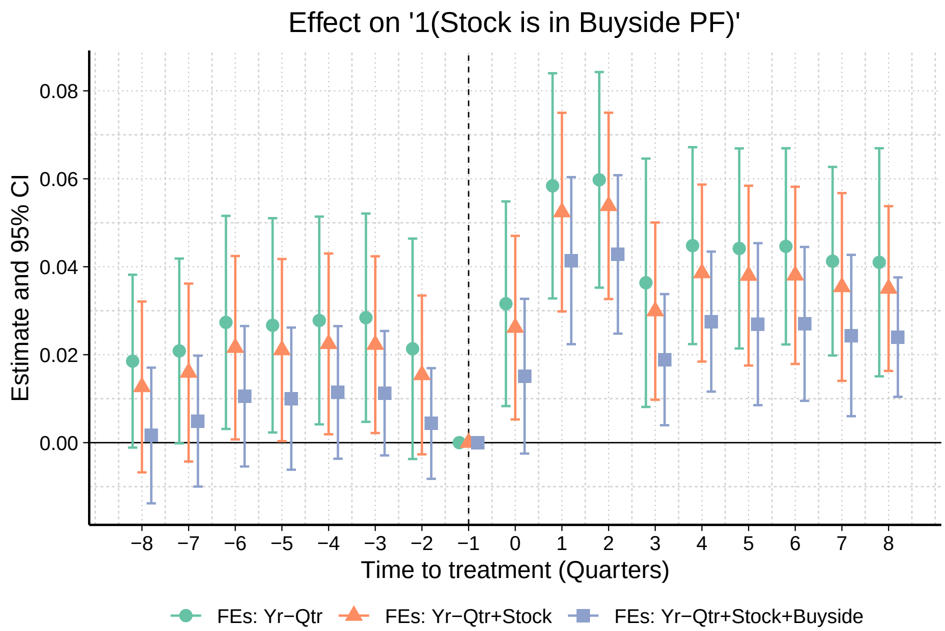
	PF Weight		% of Float in PF (x100)		MCap in PF (in $, x1000)	
	(1)	(2)	(3)	(4)	(5)	(6)
1(Treated)	0.0178***		0.0053**		249.0**	
	(0.0054)		(0.0023)		(104.8)	
1(Post)	0.0055**		-0.0002		14.06	
	(0.0025)		(0.0009)		(42.43)	
1(Treated) × 1(Post)	0.0080**	0.0081**	0.0035**	0.0036**	146.0**	147.3**
	(0.0040)	(0.0041)	(0.0016)	(0.0016)	(61.75)	(62.92)
Constant	0.0251***		0.0173***		850.9***	
	(0.0031)		(0.0047)		(214.4)	
Observations	203,677	202,266	203,677	202,266	203,677	202,266
R^2	0.0038	0.3184	0.0026	0.4906	0.0023	0.4950
Within R^2		0.0002		0.0003		0.0002
Event-time FE		✓		✓		✓
Stock FE		✓		✓		✓
Buyside Firm FE		✓		✓		✓
Analyst-by-event FE		✓		✓		✓
SE Cluster	Analy+Mgr	Analy+Mgr	Analy+Mgr	Analy+Mgr	Analy+Mgr	Analy+Mgr

(c) Include buy-side-by-year-quarter fixed effects

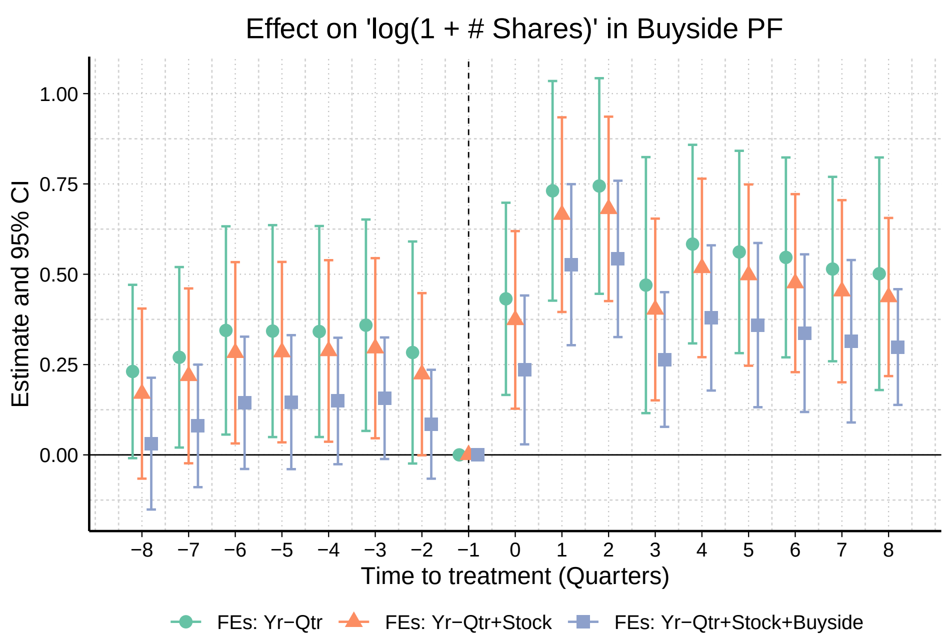
	1(In PF)	Log(1+# Shares)	% of Float (x100)	% of PF (x100)	$ Value (x1000)
	(1)	(2)	(3)	(4)	(5)
1(Treated) × 1(Post)	0.0160**	0.1932**	0.0095**	0.0029*	106.3*
	(0.0067)	(0.0834)	(0.0040)	(0.0016)	(57.21)
Observations	202,266	202,266	202,266	202,266	202,266
R^2	0.5644	0.5796	0.3470	0.5468	0.5458
Within R^2	0.0002	0.0002	0.0002	0.0002	0.0001
Event-time FE	✓	✓	✓	✓	✓
Stock FE	✓	✓	✓	✓	✓
Analyst-by-event FE	✓	✓	✓	✓	✓
Buyside-by-Yr-Qtr FE	✓	✓	✓	✓	✓
SE Cluster	Analy+Mgr	Analy+Mgr	Analy+Mgr	Analy+Mgr	Analy+Mgr

Figure 5: Dynamic effect on buy-side holdings — alternative specifications

(a) Is the stock in the buy-side firm's portfolio?



(b) Log number of shares in buy-side firm's portfolio



Notes: Analogous to Figure 2, this figure shows the dynamic effects of analyst transitions from the sell-side to the buy-side on buy-side firm portfolio holdings at the quarterly frequency. Compared to Figure 2, the displayed coefficients are estimated using different fixed effects specifications at the year-by-quarter level (green), plus stock level (orange), plus buy-side firm level (blue), as indicated.