Health constraints and analysts' strategic substitution in the research production

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Abstract

We examine *how* analysts respond to transient health constraints in their production of earnings forecasts, which we capture by the analysts' exposure to influenza. Consistent with influenza constraining research production, analysts produce less informative estimates in the high influenza areas. This effect is driven by analyst short-term forecasts – forecasts with a horizon of less than one year. In response, analysts in high influenza areas switch to producing more long-term earnings forecasts and reduce the supply of short-term forecasts. The overall supply of earnings forecasts, captured by the total count of short- and long-term earnings forecasts, remains unchanged for these analysts. The substitution effect is temporary and reverses starting from week three relative to the week we measure flu activity. The shift is concentrated (i) among analysts who face higher reputational costs for issuing low-quality forecasts, (ii) among analysts who have access to fewer resources at their brokers, (iii) when competition between analysts is lower, (iv) when the switching cost to long-term forecasts is lower, and (v) in weeks without important firm disclosure. Analysts who engage in strategic substitution during high flu times are less likely to suffer from unfavorable career outcomes. Overall, the results suggest that analysts cope with temporal research constraints driven by influenza by changing the composition of their earnings forecast supply. This strategy balances the cost of issuing less informative forecasts against the cost of a reduced supply of earnings estimates.

JEL classification: G14; M41

Keywords: Flu; analysts EPS forecasts; analyst research production

I. Introduction

This study examines strategies analysts use to respond to health-induced temporal constraints in their research production. Temporal health constraints at the analyst level are common, e.g., seasonal flu.[1] However, it is unclear what strategies analysts develop in response. Our identification uses the temporal and spatial variation in influenza that exogenously affects analysts' health and their research capability. Flu increases the cost of research directly by constraining cognitive and physical abilities and by reducing productivity (e.g., sick leave, absence from peer interactions at work and with firm management). Influenza can also affect research production indirectly through the analyst's work environment. For example, peer absenteeism reduces informal communication channels (Chen et al., 2024), can increase the need to cover for sick colleagues (increasing analyst workload), and flu can affect family members that analysts may need to take care of (Du, 2023). The result is lower quality of outputs, which when disclosed, can negatively affect analyst career outcomes (Brown et al., 2015; Fang and Yasuda, 2009; Groysberg et al., 2011; Hong et al., 2000). As influenza is exogenous to analyst and firm characteristics, we can causally link the variation in the intensity of influenza – an exogenous temporal constraint in analyst research production – to the variation in analyst research supply of earnings forecasts.

We focus on the effect influenza has on the supply of earnings forecasts, which are arguably the most important analyst research outputs (Kothari, 2001; Ramnath et al., 2008). In additional tests, we also examine the effects on the issuance of non-earnings estimates. To capture the supply of earnings forecasts, we examine the supply of short-term forecasts (forecast horizon less than and equal to one year) and long-term forecasts (forecast horizon longer than one year).

[1] The Centers for Disease Control and Prevention (CDC) reports annual symptomatic influenza cases ranging between 9.3 million and 41 million between 2010 and 2020 (https://www.cdc.gov/flu/about/burden/past-seasons.html). Keech and Beardsworth (2008) report an average of 3.7–5.9 working days lost per episode of influenza following physician diagnosis and between 1 and 4.3 days for self-reported influenza episodes.

The importance of short-term forecasts has been well-researched (Brown et al., 2015; Kothari et al., 2016; Ramnath et al., 2008). Analysts also increased the issuance of long-term forecasts over time, from 40% of all earnings forecasts in 2001 to close to 50% in 2019 (Figure 1). Market participants value long-term forecasts as these forecasts are used by analysts to generate stock recommendations (Bradshaw, 2004; Jung et al., 2012), in firm valuation (Frankel and Lee, 1998; Gebhardt et al., 2001), and to estimate the cost of equity capital (Claus and Thomas, 2001; Botosan and Plumlee, 2005). Long-term forecasts convey new information to the market and affect analyst career outcomes (Jung et al., 2012). Bradshaw et al., (2012) report that earnings forecasts with a two-year horizon are available for almost the same firms that have one-year ahead forecasts, suggesting these forecasts are commonplace at the firm level.

We propose two mutually non-exclusive strategies analysts can use to cope with temporal constraints in producing earnings forecasts due to influenza. The *pause hypothesis* suggests that analysts temporarily reduce their total supply of earnings forecasts to ensure the forecasts they issue meet the minimum quality criteria. Health constraints likely increase the cost of research and decrease forecast informativeness. As analysts build credibility for the quality of their research (Brown et al., 2015; Harford et al., 2019; Hong et al., 2000; Kothari et al., 2016), they will avoid issuing forecasts that do not meet the quality threshold. However, reducing the supply of earnings forecasts comes at a cost: (i) analysts may not satisfy the informational demand from investors (Chen and Cheng, 2006; Chiu et al., 2021), (ii) it lowers analyst visibility in the market, which can affect career outcomes (Brown et al., 2015), and (iii) it lowers forecast timeliness that can reduce the favorability of broker votes, which affects analyst compensation (Groysberg et al., 2011).[2] Analysts who reduce the supply of earnings forecasts incur these costs.

[2] Brown et al., (2015) highlight that analyst accessibility and responsiveness is among the top three considerations for analyst compensation and broker votes.

The *rebalancing hypothesis* predicts that analysts maintain their overall research output to avoid the costs associated with lower forecast supply. However, they change the proportion of short-term compared to long-term earnings forecasts. Compared to long-term forecasts, short-term forecasts have lower bias and noise (Chan et al., 2003; De Silva and Thesmar, 2024), and their quality can be ascertained relatively promptly at quarterly announcements. Analysts have more time to revise their long-term forecasts before earnings announcements, which means their long-term forecasts' ex-post quality may be less affected by the analyst's temporal cognitive inhibition due to influenza. Errors in longer-term forecasts can also be more easily ascribed to unexpected future events. Thus, the negative effect of flu on short-term forecast quality can be both proportionally larger (relative to the inherent forecast accuracy) and more visible to market participants compared to long-term forecasts. As a result, market and career penalties for inaccurate short-term forecasts are likely higher than for inaccurate long-run forecasts. This can motivate analysts to lower the proportion of short-term forecasts and increase the issuance of long-term earnings forecasts while keeping the overall supply unchanged.

Our empirical identification strategy uses temporal variation in influenza in analysts' geographic locations. We use the data from the Centers for Disease Control (CDC) on the average weekly outpatient visits to healthcare providers for influenza-like illness (ILI) in a U.S. state to measure influenza activity in an analyst location. From I/B/E/S, we collect a sample of analyst quarterly (up to three quarters ahead) and the first semi-annual forecasts that we consider short-term forecasts. Forecasts with forecasting horizon larger than one year are long-term forecasts. All other EPS forecasts (one-year-ahead, the fourth quarter ahead, and the second semi-annual ahead) are one-year-horizon forecasts. We hand-collect analyst location data from *LinkedIn* and *FINRA*'s *BrokerCheck*. To causally link influenza to analyst research production, we only select firms covered by a minimum of two analysts located in different

U.S. states. This allows us to link the variation in influenza to analyst research outcomes that is not driven by firm or macroeconomic characteristics, e.g., changes in the informativeness of firm disclosure, as the latter would affect all analysts. To strengthen inferences, we control for potential contemporaneous confounding effects by including fixed at analyst, firm-quarter-year and state-quarter-year levels. [3] This setup helps us to control for a range of potential confounding firm, analyst, macroeconomic and temporal effects that can correlate with influenza and analyst research activity.

The first set of tests validates that analyst production of earnings forecasts is affected by influenza. We focus on price reactions to forecast announcements as a measure of the informativeness of analyst research and its usefulness to investors (Brown et al., 2015; Givoly and Lakonishok, 1980; Imhoff and Lobo, 1984). Analysts collect and process public information, as well as generate and disseminate private information to the market, contributing to the price discovery process (Chan et al., 2003; De Silva and Thesmar, 2024). Gleason and Lee (2003) find that the market reacts more strongly to revisions by analysts' high-quality forecasts. As the flu comprises the quality of research, we expect and find a reduction in the market reaction to analysts' forecast revisions. Importantly, the effect is present only for short-term forecasts and one-year-horizon in some models. The flu severity reduces the impact of analysts' short-term forecast revisions on market reaction by 11–23% . To understand why the informativeness of short-term forecasts reduces, we focus on their accuracy. We document a significant reduction in the accuracy of short-term forecasts, primarily quarterly forecasts, issued by analysts in high influenza areas. A one-standard-deviation increase in flu activity leads to a 1.35% reduction in the mean accuracy for the quarterly forecasts relative to the stock price.[4] In contrast, the accuracy of long-term forecasts issued by analysts in highly influenza

[3] We show the robustness of our conclusions to alternative fixed effects structures.
[4] The sample mean stock price is $63.4, which suggests a $0.86 reduction in EPS forecast accuracy.

areas is unaffected. Thus, though the forecast error of long-term forecasts is higher than that of short-term forecasts (Bradshaw et al., 2012; Jung et al., 2012), the relative accuracy of short-term estimates reduces in comparison to long-term forecasts for analysts in high flu areas.

Next, we examine our main question on *how* the analysts' supply of earnings forecasts changes in response to the production constrains imposed by influenza. We document that analysts in high influenza areas do not alter their overall supply of earnings forecasts as captured by the total number of short- and long-term EPS forecasts. However, we observe a significant reduction in the proportion of short-term forecasts and an increase in the supply of long-term estimates. This effect is economically significant: a one-standard-deviation increase in influenza intensity associates with a 0.6% decrease in quarterly EPS forecasts, and a 0.5% decrease in EPS forecasts with a one-year horizon, a corresponding increase in the supply of long-term forecasts.[5] The evidence is consistent with the *rebalancing hypothesis* – analysts trade off short-term for long-term estimates to minimize the risk of reduced visibility and weakened standing with investors originating from lower research supply and the reputational cost from issuing lower-quality short-term forecasts.

Subsequently, we perform several sensitivity tests to validate the robustness of the conclusion. First, the temporal effect of influenza suggests we should observe a future *reversal* in the supply of forecasts to return to the long-term equilibrium. Consistently, we report a reduction in the supply of long-term forecasts and an increase in the supply of short-term forecasts starting from the third week relative to a week where we measure the intensity of flu in a state. Second, if analysts co-locate close to the firms they follow, then our results could capture changes in firm reporting quality due to flu (Chen et al., 2023). We address this concern fourfold. First, we control for the intensity of influenza in the state where the firm is

[5] The reductions in the supply of short-term forecasts are striking as we use a one-standard-deviation change in flu intensity, which would be equivalent to changes in flu between normal and pandemic-level flu intensity.

headquartered. Second, we select a sample of analysts located in a different state than the state where the firm is headquartered. Thus, the variation in the supply of forecasts is not driven by the conditions at the firm's headquarters. Third, we select only firms headquartered in states with below-median flu intensity in a week relative to other states. Finally, our fixed effect structure, which includes firm-year-quarter effects, should control for the temporal variation in reporting quality at the firm and quarter-year levels. Our results replicate in all these settings. Thus, it is not the changes in firm reporting but shocks to analyst research production that explain our results.

Next, we examine the effect of cross-sectional variation in the *external incentives to generate research* and *external monitoring of analyst research* on the substitution effect we document. Specifically, we condition the effect of influenza on the variation in firm ownership characteristics to capture the incentives to generate research stemming from analysts' clients and institutional monitoring of analyst research. First, transient investors, such as hedge funds, are among analysts' main clients as they generate substantial trading commissions and affect analyst compensation through broker votes (Brown et al., 2015). These investors focus on short returns and are concerned with the quality of analyst research about the firms they hold stock in (Mintchik et al., 2011). Analyst short-term forecasts better anticipate earnings that align with transient investors' holding periods. Thus, analysts face stronger external monitoring of their short-term forecasts in the presence of transient investors. As the accuracy of short-term forecasts is compromised due to flu, we would expect to see stronger evidence of substitution in the presence of transient investors. We confirm this prediction. Second, monitoring of analyst forecasts is likely larger for stocks with more concentrated ownership where investors have more monitoring incentives and can devote more resources to monitoring (Burns et al., 2010; Hartzell and Starks, 2003). Consistently, the substitution effect we document is stronger for stocks with more concentrated ownership.

Next, we examine the effect of the cross-sectional variation in *analyst incentives* to issue research. First, we condition the effect we document on analyst reputational capital. We find that the effect we document is weaker among newly hired analysts (analysts appearing on I/B/E/S in a new brokerage house in the first 26 weeks). Newly hired analysts need time to build reputational capital and face lower costs of issuing inaccurate forecasts. They also have strong incentives to be visible to investors by issuing forecasts, including short-term estimates (Ertimur et al., 2011). Thus, they would have fewer incentives to conduct the strategic switching, a result we confirm. Second, we expect the incentives to protect reputational capital through forecast substitution to be stronger for analysts who have accumulated reputational capital (Fang and Yasuda, 2009; Groysberg et al., 2011; Hong et al., 2000). Consistently, we find the substitution effect is more substantial for analysts in the top decile of forecast accuracy. Jackson (2005) and Kadous et al. (2009) argue that investors build beliefs about analyst skills by observing forecast accuracy. Brown et al. (2015) highlight that forecast accuracy is an important characteristic of analysts' reputation with investors.

Additional tests focus on the effects of (i) analysts' work environment, (ii) the cost of switching from short-term to long-term forecasts, (iii) the competition between analysts, and (iv) firm information events. First, we argue that analysts who are able to access more resources at the broker can moderate the negative effect of flu. For example, an analyst can temporarily delegate some of the tasks to colleagues to focus on updating their forecasts. Analysts at larger brokers or who work in teams would have fewer incentives to switch from short-term to long-term forecasts. Both effects should moderate the substation effect, a result we confirm. Second, we expect the forecast substitution will be moderated by high switching costs from short-term to long-term forecasts. If an analyst tends to provide more short-term forecasts in the past, abruptly switching to long-term forecasts may cause additional attention from investors and closer scrutiny of analyst outputs. Consistently, we find a weaker substitution effect among analysts with high switching costs. Third, we argue that competition between analysts for investor attention should incentivize analysts to produce more short-term forecasts moderating the effect we document (Hong and Kacperczyk, 2010; Mikhail et al., 1999; Stickel, 1992; Wang et al., 2020). Consistently, the substitution effect is weaker for stocks with higher analyst coverage, where the competition between analysts is likely more intense. Finally, analysts are incentivised to quickly update their forecasts following major corporate events (Shroff et al., 2014). Past research attributes forecast timeliness to better career outcomes and more favorable broker votes directly affecting analyst compensation (Groysberg et al., 2011). We expect analysts to have a strong incentive to update their forecasts, including short-term forecasts, following major corporate events, which can moderate the effect we document. Consistently, we do not find evidence of a reduction in the supply of short-term forecasts or an increase in the production of long-term forecasts in weeks when a company announces quarterly earnings figures or issues earnings guidance. Substitution is present in weeks without important firm disclosure events.

Our next test explores the impact of analysts' strategic substitution on analyst career outcomes. Prior literature documents that analysts' poor forecast performance leads to negative labor market consequences (Groysberg et al., 2011; Hong et al., 2000; Hong and Kubik, 2003; Leone and Wu, 2007; Mikhail et al., 1999; Stickel, 1992). We document that analysts issuing fewer short-term forecasts and more long-term forecasts during periods of high flu activity are less likely to move to a lower-tier brokerage house in the next 12 months. This evidence is consistent with the strategic substitution we document hedging analysts against unfavourable career outcomes.

To close the loop, we examine whether our findings extend to forecasts of other financial items beyond EPS estimates. We find a similar switching pattern for the gross margin forecast, EBIT and EBITA, pre-tax profit, net income and GAAP EPS forecast. For forecasts with arguably lower reputational costs associated with issuing inaccurate estimates, such as the net asset value, dividend per share, and return on assets, we only find an increase in the supply of long-term forecasts. Finally, for industry-specific forecasts, such as funds from operations specific to the real estate industry, there is no evidence of changes in the supply of either short-term or long-term forecasts. This completes the picture of analysts' strategic switching.

The study contributes to the literature on how analysts cope with temporal health constraints affecting their research production. Previous research suggests that analysts *reduce* research activity when they face research processing constraints. Pisciotta (2023) reports that an increase in analyst workload, captured by analyst allocation to cover an IPO firm, reduces the accuracy, the number and timeliness of forecasts. Driskill et al., (2020) report that analysts are less likely to issue timely forecasts when there are several firms in the coverage portfolio announcing on the same day. Dehaan et al. (2017) report that weather-induced negative mood reduces the timeliness of analyst forecasts within three days of earnings announcements compared to analysts in pleasant weather locations. The Blankespoor et al. (2020) review of the disclosure processing costs literature highlights that analyst research suggests that '[C]eteris paribus, analysts are less likely to forecast when experiencing capacity constraints.' Studies also focused on the quality of outputs when analysts face research constraints. Hirshleifer (2019) report that analysts suffering from decision fatigue issue less accurate forecasts. Dong et al., (2021) document that analysts who visit companies in severely polluted areas suffer from a 'bad mood' and issue less favorable forecasts. Our results suggest that the response to temporal processing constraints is more nuanced – analysts strategically substitute short-run earnings forecasts, which are less accurate when analysts are suffering from influenza, for long-run forecasts that are comparatively less affected. Our paper differs from past evidence that focuses on documenting that analysts suffer from capacity constraints.[6] We examine the strategies analysts use to address temporary capacity constraints, which adds novel results to the literature. Little is known about the strategies analysts use to address temporal constraints in research production. Our findings should help to spur future research into understanding what strategies analysts use in response to both analyst-level and firm-level shocks that affect their research production.

Our results are important considering that analysts are key information intermediaries in the market. Analyst research coverage benefits firms through lower cost of capital and financial constraints (Derrien and Kecskés, 2013; Leuz and Wysocki, 2016), lower information asymmetry between managers and outside investors and lower agency costs (Chung et al., 1995; Chung and Jo, 1996), and higher stock visibility to institutional ownership (Bushee and Noe, 2000; Merton, 1987). Stocks covered by analysts tend to have higher institutional ownership (Bushee and Noe, 2000; Merton, 1987). Firms value analyst research and are willing to pay for analyst coverage (Billings et al., 2014; Kirk, 2011) and hire investor relations professionals to pitch their business to analysts (Bushee and Miller, 2012). Analyst research is also important to investors for their investment strategies (Barber et al., 2001; Jegadeesh et al., 2004; Womack, 1996), and because it reduces investors' information acquisition and processing costs (Barth et al., 2001; Bhushan, 1989), monitoring cost (Moyer et al., 1989), and reduces instances of earnings management and fraud (Dyck et al., 2010; Yu, 2008). Our research opens avenues for future studies to understand how temporal changes in the supply of analyst forecasts affect these firm and investor outcomes.

[6] For example, Driskill et al. (2020, 165) abstract ends with 'Overall, our evidence suggests that even financial analysts, who serve as information specialists, are subject to limited attention.'

The remainder of this paper is organized as follows. In the next section, we outline the research design and variables. Section 3 describes the sources of data collection and the general sample. Section 4 reports results and findings. Section 5 concludes.

II. Research design

This section presents the research design for the empirical analysis. We initially validate the prediction that influenza affects analyst research ability and reduces the forecast quality. Next, we discuss our main tests examining how analysts respond to temporal constraints in their research production due to flu. We also present the test that examines the effect the substitution strategy has on analyst career outcomes.

2.1 Influenza and the analyst forecast quality

2.1.1 Informativeness of analyst forecasts

To validate that influenza affects the quality of analyst research, we first measure the relation between influenza and price reactions to revisions in analyst forecasts. This test captures the informativeness of analyst research (Brown et al., 2015; Givoly and Lakonishok, 1980; Imhoff and Lobo, 1984). To understand how flu affects quality of forecasts with different horizon, we classify earnings forecasts of one-quarter, two-quarters and three-quarters ahead and one-year-ahead as short-term earnings forecasts, and earnings forecasts with forecast horizon longer than two years, including long-term growth forecasts, are classified as long-term earnings forecasts. [7] Because of the importance of one-year-ahead earnings forecasts, we examine them separately from other short-term earnings forecasts. We then calculate revisions in forecasts during the fiscal year at the analyst-firm level. Specifically, $FREV_{ijt}$ is the forecast

[7] Short-term forecasts are those labelled by *IBES as having FPI* equal to 6, 7, 8, or A. Long-term forecasts are those with *IBES FPI* equal to 0, 2, 3, 4, 5, 10, C, D, E, F, G, N, O, P, Q, R, S, T, L, H, I, J, K, Y, Z, or X. We do not include long-term earnings growth (FPI=0) forecasts in the analysis as their accuracy is difficult to assess. Firms do not disclose actual growth numbers to compare against analyst long-run growth estimates.

revision by analyst j for the firm i on the day t. We then interact the forecast revision with our measure of flu intensity, FLU_{jt}, which is the weekly-level flu activity of the states where an analyst resides in the week when the analyst makes a forecast. The dependent variable is a three-day [0 +2] CRSP market value adjusted cumulative abnormal return (CAR_{ijt}). We delete forecasts made by multiple analysts on the same day. We run the regression for each forecast group, i.e., separately for short-term and for long-term forecasts. Then the regression model is as follows:

$$\begin{aligned} CAR_{ijt} &= \alpha_0 + \alpha_1 FLU_{jt} + \alpha_2 FREV_{ijt} + \alpha_3 FLU_{jt} \times FREV_{ijt} \\ &\quad + \boldsymbol{AnalystControls} + \boldsymbol{FirmControls} + \ Fixed\ Effect + \varepsilon_{ijt}. \end{aligned} \tag{1}$$

We include a set of analyst and firm control variables previous research associates with forecast quality. Analyst characteristics include analysts' firm-specific experience (*FEXP*), defined as the number of weeks since the analyst provided her first forecast for the firm, and general experience (*GEXP*) defined as the number of weeks since the analyst provided her first forecast ever (Clement 1999; Mikhail et al. 1997). We include the numbers of firms and industries that the analyst covers (*NUMFIRM* and *NUMIND*) to capture analyst workload (Clement 1999). We control for the natural logarithm of the number of days from the time when the forecast is provided to the time when the firm's earnings is released (*lnHOR*). Forecasts issued earlier in the year tend to be less accurate compared to those issued closer to the fiscal year-end (Clement 1999). We also control for analysts' past forecast accuracy (*PASTACC*) to capture the analyst reputational capital for issuing accurate forecasts (Hong and Kubik 2003).

Firm-related control variables include the market value of equity in the natural logarithm form (*lnMV)*, total analyst following (*AF*), the market-to-book ratio (*MB*), financial leverage (*LEV*), the return on assets ratio (*ROA*), and the intangible assets scaled by total assets (*INTA*) to control, as well as institutional ownership (*INST*), Firm characteristics are measured one quarter before. We consider a different fixed effects structures to showcase robustness of our results. The first model includes forecast horizon fixed effects, firm-fixed effects, analyst-fixed effects and quarter-year-fixed effects. The second model includes analyst-fixed effects, firm-year-quarter fixed effects and state-year-quarter fixed effects. We saturate the model with several fixed effects to capture possible unobservable characteristics that can correlate with flu and intensity of analyst research. We winsorize all variables at 1% and 99% level, and cluster standard errors at the firm and the analyst level.

2.1.2 Accuracy of analyst forecasts

To dig into why forecast informativeness may change, we also examine the effect influenza has on the accuracy of analyst earnings forecasts. We expect flu to reduce average forecast accuracy. We calculate earnings forecast error ($FORERROR_{ijt}$) as the absolute difference between the earnings forecast made by analyst *j* for the firm *i* on the day *t* and the actual earnings value of firm *i*, scaled by firm *i*'s stock price at the beginning of the forecasting quarter. Forecast errors measure the inverse of forecast accuracy. We then relate flu to errors in analyst earnings forecasts for different forecasting periods: analyst quarterly forecasts (up to three quarters ahead), long-horizon forecasts and one-year-ahead forecasts. The analyst-level and the firm-level control variables, as well as the fixed effect structures are the same as in the model (1). The regression model we use to link flu to forecast errors is as follows:

$$FORERROR_{ijt} = \gamma_0 + \gamma_1 FLU_{jt} + \boldsymbol{AnalystControls} + \boldsymbol{FirmControls} + Fixed\ Effect + e_{ijt}. \tag{2}$$

The regression is estimated at the level of each forecast issued by an analyst for a firm in a fiscal year.

2.1.3 Peer perceptions of the analyst forecast quality

The price reaction tests focus on the market perceptions of the analyst forecast quality. To complement this test, we also examine if other analysts recognize that analysts in high flu states issue lower quality earnings forecasts. This test is useful as it captures perceptions about research quality from analyst peers, which should more quickly understand if quality of some analysts' forecasts deteriorates. For this test, we follow Cooper et al. (2001) and calculate the lead-follow-ratio. Specifically, we compare analyst *j*'s forecast for the firm *i* made at the time *t* with other analysts that precede and follow the publication of the analyst's *j* forecast. Leading Days (Following Days) equals the total number of days between analyst *j*'s forecast for the firm *i* issued on the day *t* and two most recent proceeding (following) forecasts made by other analysts. Then lead-follow-ratio, LFR_{ijt}, is the ratio of Leading Days scaled by Following Days. Larger *LFR* indicates leaders that other analysts herd on, i.e., other analysts issue their forecasts shortly after the leader's forecasts. Peer analysts are quicker to revise their forecasts following a lead analyst revision resulting in a higher value of the ratio (Cooper et al., 2001; De Franco and Zhou, 2009). We then use the lead-follow ratio as the dependent variable in equation (2).

2.2 Influenza and the number of short-term and long-term earnings forecasts

Next, we examine our main research question on how analysts respond to temporal constraints in research production. Our first test focuses on the total supply of short- and long-term earnings forecasts. Specifically, $NUMTOT_{\boldsymbol{ijt}}$ ($NUMTOT\_RAW_{\boldsymbol{ijt}}$) measures the natural logarithm form (or pure count) of the total number of short-term and long-term earnings forecasts for firm *i* made by analyst *j* in the week *t*. The *pause hypothesis* predicts that temporal research constraints due to flu will reduce the overall supply of analyst earnings forecasts. The *rebalancing hypothesis* suggests that analysts maintain the overall supply of forecasts and we should observe no association between flu and total research production.

The *pause hypothesis* suggests both the supply of short-term and long-run forecasts reduces. The *rebalancing hypothesis* suggests that analysts reduce the supply of short-term forecasts and increase the production of long-run estimates to keep the total supply constant. To distinguish between the two explanations, we examine the effect of flu separately for short-and long-run EPS forecasts. $NUMSHORT_{ijt}$ is the natural logarithm form of the number of short-term forecasts and $NUMLONG_{ijt}$ the number of long-run forecasts in the natural logarithm form. We also express these numbers in percentages by scaling by the total number of short-run and long-run earnings forecasts. $NUMSHORT\_PC_{ijt}$ is the percentage of short-term EPS forecasts issued by an analyst for a firm in a week and $NUMLONG\_PC_{ijt}$ is the percentage of long-run forecasts issued by an analyst for a firm in a week. We then use the total and individual counts of short-run and long-run EPS forecasts as dependent variables in Equation (2) and estimate the model at the firm-analyst-week level.

2.3 Influenza effect of substitution on analysts' career outcome

Finally, we present the research design for the effect of forecast substitution on analysts' career outcomes. Analysts with low quality forecasts are more likely to experience less favorable career outcomes. To identify career outcomes, we focus on analysts who have changed their brokerage houses in the 12-month window relative to the month we measure flu intensity by checking the broker IDs in I/B/E/S recommendation file. We then create a variable $MOVEDOWN_{jt}$ (or $MOVEUP_{jt}$), which is a dummy variable equal to one if an analyst j moves from a large (small) brokerage house to a small (large) brokerage house in the next 12 months, and is zero otherwise. A large brokerage house is defined as employing above the median number of analysts relatively to all brokerage houses in that year. Next, we create a variable $CHSHORT_{jt}$ ($CHLONG_{jt}$), which measures the monthly average percentage change in the analyst issuance of short-term (long-term) forecasts across all firms an analyst covers. We then interact changes in forecast issuance with FLU_{jt}. The model is estimated at the analyst-month-year level and includes year-month fixed effects. The regression is estimated using a logit model and is as follows:

$$MOVEDOWN_{jt}\ (or\ MOVEUP_{jt})$$
$$= \theta_0 + \theta_1 FLU_{jt} + \theta_2 FLU_{jt} \times CHSHORT_{jt} + \theta_3 FLU_{jt} \times CHLONG_{jt} \quad (3)$$
$$+ \boldsymbol{AnalystControls} + \ Fixed\ Effect + \omega_{jt}$$

III. Data and sample

We measure weekly flu activity at the analyst's location to capture analyst exposure to influenza from 2016 to 2019. We obtain the weekly state-level flu activity from the Centers for Disease Control (CDC) website (Chen et al., 2023). The CDC calculates weekly flu activity by the number of influenza-like-illnesses (ILI) cases reported by healthcare providers scaled by the number of total outpatient visits to healthcare providers in a state. The CDC definition of ILI are cases with symptoms that include fever (a temperature of 100°F/37.8°C or greater) and cough and sore throat without a known cause other than influenza. Healthcare providers report influenza voluntarily to the CDC. Jennings et al. (2023) report that ILI is measured on a consistent basis across states and time. CDC estimates that flu has resulted in 9.3 million – 41 million illnesses, 100,000 – 710,000 hospitalizations and 4,900 – 51,000 deaths annually between 2010 and 2023.[8] Typically, a peak of influenza associates with ILI above 2.1%. Off-peak level of ILI is around 1.4%. Higher ILI reflects a higher severity of flu, which can affect analysts directly (feeling unwell with a possibility of hospitalization) or indirectly (flu affecting family members and peers at work).

We hand-collect analysts' workplace locations as follows. Firstly, we download the *I/B/E/S* recommendation file for the sample period 2016 to 2019.[9] The *I/B/E/S* recommendation file contains analysts' first names initials, surnames, and brokerage houses. We use this information,

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[8] See https://www.cdc.gov/flu-burden/php/about/index.html?CDC_AAref_Val=https://www.cdc.gov/flu/about/burden/index.html.
[9] We start the sample in 2016 and end it in 2019 to reduce the cost of analysts' identification.

and a list of firms covered by the analyst, to find the analyst's full name on *Bloomberg*. We next manually search for full names on *LinkedIn* and upon finding the analyst's *LinkedIn* profile page we record their historical workplace locations (Bradley et al., 2017). If we cannot find an analyst's historical workplace location on *LinkedIn*, we use *FINRA*'s *BrokerCheck* website instead. We removed analysts located in Florida as the flu activity data for this state is not available on the CDC website. We successfully identify locations of 2,402 US-based analysts.[10] We then collect analyst earnings forecasts from I/B/E/S over the period 2016 – 2019 that we classify into short-term (I/B/E/S FPI = 6, 7, 8, or A) and long-term (I/B/E/S FPI = 0, 2, 3, 4, 5, 10, C, D, E, F, G, N, O, P, Q, R, S, T, L, H, I, J, K, Y, Z, or X). In addition, we also categorize the remaining forecasts (I/B/E/S FPI = 1, 9 or B) as the one-year-horizon group to complete the classification. Accounting information is from *COMPUSTAT*, stock price data from *CRSP,* and institutional ownership from *Thomson Reuters 13F*. In further tests, we split investors using the classification from Brian Bushee's website.[11] After deleting missing observations, the final sample includes 385,997 analyst-week-firm forecasts over the period 2016-2019 with 2,047 unique analysts and 3,374 unique firms.

Figure 1 reports the proportion of short-term forecasts, long-term forecasts and one-year-ahead forecasts over the sample period. We observe that the proportion of long-term forecasts increases from around 4% of all earnings forecasts in 2001 to close to 50% in the last years of the sample period. This result suggests that long-term forecasts make up a significant proportion of the total supply of earnings forecasts. The proportion of quarterly forecasts ranges between 33% in 2001 and 28% in 2019. The proportion of one-year-ahead forecasts reduces from 27% in 2001 to 25% in 2019.

[Figure 1 here]

[10] During the sample period, 81 analysts have relocated across the states. The number of unique analysts is 2,321.
[11] The website of Brian Bushee: https://accounting-faculty.wharton.upenn.edu/bushee/

3.1 Descriptive statistics

Table 1 Panel (A) reports the distribution of analysts across states. More than 50% of analysts are based in New York, followed by California, Texas, and Illinois. This evidence is consistent with previous research (Jennings et al., 2017; Malloy, 2005). Malloy (2005) reports that 56.47% of analysts in his sample are located in New York. Panel (B) of Table 1 presents the distribution of our baseline construct — average weekly influenza activity – across states where at least one analyst resides. Texas has the highest average weekly flu activity, followed by Louisiana and Georgia.

[Table 1 here]

As a first-cut tests, we examine the proportion of long-term forecasts across flu deciles based on the split across the entire sample period. Figure 2 shows that the weeks with the highest flu activity have generally more long-term forecasts than short-term estimates.

[Figure 2 here]

The averages flu activity across states reported in Table 1 do not capture temporal differences in flu. Figure 3 Panel (A) reports the intensity of flu across the calendar months. We observe that flu peaks tend to occur in January, February and December. This is also consistent with CDC data that 'During this 40-year period [1982-2022], flu activity most often peaked in February (17 seasons), followed by December (7 seasons), January (6 seasons) and March (6 seasons).'[12] Figure 3 Panel (B) reports temporal variation from 2016 to 2019 We observe higher severity in the year of 2019. This evidence is consistent with CDC's data that the years 2014-15, 2017-18 and 2019-20 had higher flu severity compared to the average.[13]

[Figure 3 here]

[12] https://www.cdc.gov/flu/about/season/index.html
[13] https://www.cdc.gov/flu/about/keyfacts.htm

Table 2 reports the descriptive statistics for all variables used in this paper reported on an analyst-week-firm level. Panel (A) reports the mean number of all earnings forecasts, regardless of forecast horizons, is 6.5 per firm per week. This is comparable with Bradshaw et al. (2012). On average, analysts issue 2.1 short-term EPS forecasts per firm per week (33% of all forecasts), 3.0 long-term estimates (43%). Thus, a substantial proportion of all forecasts reports by analysts include forecasts with a horizon longer than one year ahead, consistent with Balashov and Pisciotta (2023); Bradshaw et al. (2012); and Jung et al. (2012). As one-year-ahead forecasts have been the focus of a significant portion of the literature, we also report their number separately, which is 1.4 (24% of all forecasts).[14]

Panel (B) shows the flu intensity measure, which averages 2.185 meaning 2.185 patients among 100 patients develop influenza-like-illnesses. This is comparable with Chen et al. (2023). Panel (C) reports analyst characteristics. The average analyst's general experience is 735.7 weeks (equivalent to 14.1 years) and firm-specific experience is 255 weeks (equivalent to 4.9 years).[15] These values are comparable with earlier research (Bradley et al., 2017; Keskek et al., 2017). An average analyst follows 21.5 firms and 3.5 industries, similar to the results in Driskill et al. (2020) and Fang and Hope (2021). Mean past accuracy, which captures an analyst relative ranking in terms of accuracy compared to peers is 50.77. Past accuracy ranks analysts on scale from 1 to 100. A mean of 50.77 reflects that an average analysts is close to the median value on past accuracy (Chang et al., 2023; Driskill et al., 2020).

Panel (D) reports firm characteristics. On average, around 46.7% of forecasts are issued in a week that includes a quarterly earnings announcement of which 11.9% includes the release of annual results. This finding is consistent with (Altinkiliç et al., 2013; Hsu and Wang, 2021;

[14] The values of *NUMSHORT*, *NUMLONG*, *NUMONEYEAR* are in the natural logarithm forms. The means are 1.039, 1.208, and 0.33. In the untabulated table, the mean of pure counts of *NUMSHORT*, *NUMLONG*, *NUMONEYEAR* are 2.12, 2.99, and 1.43.

[15] We measure analyst characteristics using all I/B/E/S data starting from 1980 where the first forecast appears in I/B/E/S.

Li et al., 2015). The average log market capitalization is 2.074 consistent with analysts covering larger firms (Chang et al., 2006). Mean leverage of 0.612, ROA is 1.2%, market-to-book ratio is 4.09, and asset-scaled intangibles are 0.199. These results are comparable with previous studies (Driskill et al. 2020; Hsu and Wang 2021(Driskill et al., 2020; Hsu and Wang, 2021). Institutional ownership averages 77.7%, consistent with analysts covering stocks with larger institutional presence (O'Brien and Bhushan, 1990) and on average there are over 18 analysts following a firm.

[Table 2 here]

IV. Regression results

Our first tests validate the prediction that flu reduces the forecast quality. Subsequently, we present the main regression results on the link between research production constraint due to flu and analyst research production.

4.1 Flu and forecast quality and market reaction

Gleason and Lee (2003) find that stock market recognizes analysts' forecast quality and reacts more strongly to revisions by analysts' high-quality forecasts. If flu decrease analysts' short-term forecast quality, then it would have a moderating effect to market reactions to analyst forecast revisions. Table 3 Panel (A) reports the results for Equation (1). Columns (i) to (iv) focus on the short-term quarterly forecasts, while columns (ii) and (v) cover long-term forecasts. Columns (iii) and (vi) include one-year-ahead forecast errors to offer a complete view of the impact of flu. we find a positively significant coefficient on *FREV* in all models. This is consistent with Gleason and Lee (2003) that stock market reacts to analysts' forecast revisions. Importantly, the interaction term of *FLU×FREV* is negatively significant for quarterly forecasts and one-year-ahead forecasts. This result suggests that the market perceives that flu reduces informativeness of analyst forecasts suggesting a decrease in analysts' short-term forecast quality. In contrast, we do not find any moderation effect in the long-term forecast revisions as they remain the same quality.

To understand why informativeness of short-term forecasts reduces, Panel (B) presents the regression results for the relation between flu severity and analyst forecast error, an inverse measure of forecast accuracy. The results suggest that short-term forecast errors increase with flu severity. Specifically, a one-standard-deviation increase in flu severity, measured by weekly outpatient clinic visits due to flu, is associated with a rise of 1.35% of the mean short-term forecast error. This evidence suggests that at least one reason why the informativeness of short-term forecast reduces, is because influenza reduces the accuracy of these forecasts. However, this negative impact appears to be limited to short-term forecasts. Forecast accuracy for long-term horizons does not decline with flu severity. Both the results from forecast quality and from market reaction validate the analysts' incentives to conduct strategic substitution under the flu intensive period.

[Table 3 here]

4.2 Flu and analyst research production

Next, we move to our main tests that examine *how* analysts respond to the temporal constraints in research production due to flu. First, we link flu to the *total* supply of analyst earnings forecasts of various horizon. Panel (A) of Table 4 reports no association between the severity of flu in a state and analyst total supply of forecasts when we use both raw counts and natural logarithm transformation of forecast count. This effect is consistent for various fixed-effect structures including firm-, quarter- and analyst-fixed effects and firm times quarter and state times quarter. Thus, even saturating the model with various fixed-effect structures leaves our conclusion unchanged. Thus, it is unlikely that omitted correlated variables could affect the conclusions. Overall, there is no evidence supporting the ‘pause hypothesis’ that analysts reduce the number of forecasts during high flu season.

Panel (B) evidence is seemingly at odd with the findings in Table 3. Past literature suggests low-quality forecasts can negatively impact the analyst's reputational capital and career outcomes (Brown et al., 2015; Fang and Yasuda, 2009; Groysberg et al., 2011; Hong et al., 2000). To dig deeper, we examine separately the supply of short-term and long-term EPS forecasts. Panel (B) of Table 4 reports that analysts reduce the supply of short-term forecast but increase the supply of long-term forecasts in response to flu severity. This points to a strategic substitution between EPS forecasts of different horizon. Table 3 suggests that quality of short-term estimates is relatively more negatively affected by flu. Thus, analysts rationally switch to producing comparatively more accurate long-term estimates. This substitution also allows them to avoid the costs of reducing the supply of earnings forecasts and minimize the cost of issuing relatively less accurate short-term than long-run forecasts. Overall, the evidence in Panels (A) and (B) is consistent with the rebalancing hypothesis.

As a robustness check, Panel (C) of Table 4 examines the logarithm of the number of each type of forecast instead of their shares. These models also include the logarithm of the total number of forecasts issued as a control variable to ensure that the *FLU* coefficient captures changes in the number of short-term and long-term forecasts, *given a constant total number of forecasts*. The results in Panel (C) show that severe flu increases the number of long-term forecasts and decreases the number of short-term forecasts for a given total number of forecasts issued, reinforcing the findings from Panel (B).

In summary, Table 4 demonstrates that during the high flu season, analysts continue to maintain their overall research output but strategically substitute short-term forecasts with long-term forecasts. This evidence supports the rebalancing hypothesis rather than the pausing or reorienting hypotheses.

Given our agnostic approach regarding whether one-year-ahead forecasts should be classified as short-term or long-term, Columns (vii) to (ix) in Panel (B) examine the effect of flu severity on the share of one-year-ahead forecasts. The results indicate a negative relationship between flu severity and the share of these forecasts. Similarly, when the log number of one-year-ahead forecasts is used as the dependent variable in column (iii) in Panel (C), the findings remain consistent. The negative coefficient for *FLU* suggests that analysts might treat one-year-ahead forecasts as a type of short-term forecast, even though the one-year-ahead earnings forecast accuracy does not decrease. Moreover, since short-term, one-year-ahead, and long-term forecasts collectively constitute the total number of forecasts by an analyst, the sum of the coefficients in Panel (B) from the same specification should theoretically approximate zero. For example, the sum of the coefficients for the short-term forecast in Column (i) (-0.193), the one-year-ahead forecast in Column (vii) (-0.253), and the long-term forecast in Column (iv) (0.446) equals zero, as expected.

[Table 4 here]

4.2.1 Reversal in the supply of forecasts

If flu generates a *temporal* constrain in analyst research production, we should observe a *reversal* in the supply of forecasts and a return to the long-term equilibrium over subsequent weeks. Though we do not have the exact timing when analysts will experience negative effects of the flu, keeping analyst, firm and temporal effects constant, we should observe a future reversal for a specific analyst-firm-week pair relative to the current week flu activity. We test this prediction in Table 5 where we regress analyst percentage supply of short-term and long-run forecasts one, two, three and four weeks ahead on the current week when we measure flu activity. We observe a reversal in the supply of forecasts starting from week 3: analysts increase the supply of short-term forecasts and reduce the supply of long-run estimates. These findings confirm the reversal of the substitution effect in EPS forecasts of different horizon.

[Table 5 here]

4.2.2 Addressing the concern of confounding effects at the firm level

Table 4 conducts several robustness tests to ensure that our results are not driven by confounding effects at the firm level. One potential confounding factor is the local flu severity around a firm's headquarters. Chen et al. (2023) document that high local flu severity can lead firms to issue more long-term corporate guidance. If analysts co-locate close to firms and respond to the firm's guidance by updating their long-term forecasts, this could create a positive relationship between flu severity and the share of long-term forecasts.

We address this concern using three approaches. First, we control for flu severity at the firm’s headquarters location (*FLU_FIRM*). Columns (i) and (ii) in Table 6 show that flu severity at the headquarters has similar effects on the share of short- and long-term forecasts as the flu severity at the analysts' location. Specifically, high flu activity at the firm’s headquarters increases the proportion of long-term forecasts and decreases short-term forecasts. However, we continue to find significant coefficients for *FLU* with the consistent sign for short-term and long-term forecasts and of larger magnitude than on *FLU_FIRM*. This evidence suggests that flu severity at the analysts’ location has a stronger impact on their forecasting output than at the firm's location. Further, in untabulated results, we find that the coefficient magnitudes are statistically indistinguishable from Table 4. Thus, controlling for flu at firm’s location does not change the tone of our results.

Second, we examine a subsample where analysts and firms they cover are located in different states than the state where the firm’s headquarters is located. In this case, the flu measure should only capture the flu severity around the analysts’ locations, not the firm. Columns (iii) and (iv) present the results for this subsample, which remain consistent, with the coefficients of interest statistically significant at the 1% level and similar in magnitude to those in Columns (i) and (ii).

Third, we analyze an alternative subsample of firms located in low-flu severity states, defined as states with weekly flu severity below the median level. By focusing on these low-flu severity states, we minimize the confounding influence of the firm's local flu conditions. Although the number of observations roughly halves, as reported in Columns (v) and (vi), the coefficients for *FLU* remain both statistically and economically similar to those in the earlier columns. These complementary approaches demonstrate the robustness of our findings and help rule out the confounding effects of firm-specific and macroeconomic characteristics.

[Table 6 here]

4.3.1 Flu and institutional pressure

Next, we present cross-sectional evidence suggesting that concerns about reputational loss, peer pressure, and client information demand underpin the strategic substitution of forecasts. Analysts cater primarily to institutional investors (Bilinski et al., 2018; Chiu et al., 2021; Gu et al., 2013). Thus, they have to consider the information needs and institutional pressure to generate research of interest to their clients. As a result, investor demand for analyst research can influence strategic substitution. We use two cross-sectional tests to tease out the institutional effect on the substitution strategy we document. First, short-term investors place more value on short-term forecast accuracy. These investors focus on short returns and are concerned with the quality of analyst research about the firms they hold stock in (Mintchik et al., 2011). Such investors are also among analyst main clients due to significant trade commission they pay (Brown et al. 2015). Analysts may face potentially greater reputational damage for issuing low-quality short-term forecasts if these forecasts are used and assessed by a large number of short-term investors (Bilinski et al. 2018). Consequently, analysts have stronger incentives to substitute short-term forecasts with long-term forecasts for firms with higher short-term ownership. To test this prediction, we identify short-term ownership using the classification from (Bushee 2001). The variable *HighTrans* equals one if a firm's short-term ownership is above the median. We then interact the measure with *FLU*. Panel A of Table 7 reports the descriptive statistics for the portioning analysis we perform in Table 7. The results in columns (i) and (ii) of Panel (B) in Table 7 indicate that during high flu seasons, analysts also substitute more short-term forecasts with long-term ones for firms with more short-term investors who value short-term forecast accuracy.

Second, the scrutiny of analyst forecasts is likely larger for stocks with more concentrated or block ownership. Investors with block ownership of a firm may rely more on their own channel for the information acquisition than on analysts' research. This reflects that blockholders have less monitoring incentives and can devote less resources to monitoring of analyst research compared institutions with more diversified and less concentrated holdings (Burns et al., 2010; Hartzell and Starks, 2003). Thus, for stocks with more block ownership, the substitution effect should be stronger. We create a measure *HighBlock*, which takes a value of one if a firm's block holdings is above the median level. We then interact this measure with *FLU*. The columns (iii) and (iv) in Panel (B) of Table 7 confirm this prediction – the coefficient on the interaction terms between flu and measure of block ownership in a stock is negative for short-term forecasts and positive for long-run estimates.

4.3.2 Flu and analysts' brokerage house resources

Analysts' access to more resources at the broker can moderate the negative effect of flu. For example, analysts suffering from flu can temporarily delegate some of the tasks to colleagues to focus on updating their forecasts. Analysts at larger brokers can also face more pressure from their institutional clients to issue short-term forecasts. Both effects should moderate the substation effect. To test this prediction, we create two variables (1) *HighBro* that takes a value of one if the number of analysts of the employing broker is above the median in the given year, and zero otherwise, and (2) *TeamAn* that takes a value of one if the I/B/E/S ID covers more than 40 firms in a 12-month period. The forecasts under such I/B/E/S ID are very likely to be provided by an analyst team (Kini et al., 2009). We then interact these measures with *FLU*. The coefficients in the columns (i) to (iv) of Panel (C) in Table 7 on the interaction terms suggest the effect of flu is weaker for analysts employed by larger brokers and for analyst teams. In addition, we also partition the sample by analysts who just switch their employing brokerage houses. These newly hired analysts, defined as those provide forecasts within 26 weeks (half a year) from the first forecast made within the new broker, are very likely to be still adapting to the new work environment and have less incentive to conduct strategic substitution. We then interact the indicator for these analysts (*NewHired*) with *FLU*, and find alleviated coefficient on the interaction term in columns (v) and (vi), which confirms our prediction.

4.3.3 Flu and analyst reputation concerns

Analysts with higher forecast accuracy, who have more reputational capital to protect, are expected to be more likely to substitute short-term forecasts with long-term forecasts. We focus on past forecast accuracy following the evidence in Keskek et al. (2017) who document that after the Global Settlement, past forecast accuracy is a stronger predictor of analyst skill than other proxies like analyst forecasting experience, broker size, and All-Star status. Analyst skill and forecast accuracy correlate with the analyst reputation and career outcomes (Hong et al., 2000; Hong and Kubik, 2003). We categorize analysts into two groups based on their past forecast accuracy, with the *HighScore* group representing the top 25% in terms of forecast accuracy. We then interact the *FLU* measure with an indicator variable for *HighScore* to assess how the impact of flu severity varies with past forecast performance. Column (i) in Panel (D) of Table 7 shows a negative coefficient for the interaction term, indicating that analysts with strong past performance – larger reputational capital – reduce the share of short-term forecasts more during high flu seasons. Conversely, Column (ii) in Panel (D) reveals that these analysts also increase the share of long-term forecasts more during the same period. Overall, Columns

(i) and (ii) suggest that analysts with larger reputational capital engage in more strategic substitution during high flu seasons.

Next, we examine the effect of analysts' short/long-term switching cost on the substitution effect. The abrupt short/long-term switching may catch much attention and suspicion from the investors and other analysts. Thus, analysts bearing high switching cost are less likely to conduct strategic substitution. We define a dummy variable – *HighSCost* – with the value of one if an analyst's switching cost (short-term to long-term forecasts) is high, and zero otherwise. Analysts' switching cost is defined as follows: (1) we calculate the percentage of analysts' short-term forecast numbers in the previous two months; (2) *HighSCost* equals to one if the previous short-term forecasting percentage in (1) is higher than median level, and zero if the previous short-term forecasting percentage is less than the median level or analysts do not provide any forecasts in the previous 2 months. We then interact *HighSCost* with *FLU* and report the results in columns (iii) and (iv) of Panel (D) in Table 7. Consistent with our prediction we find a positive (negative) coefficient on the interaction term on the short-term (long-term) leg, suggests analysts with high switching cost engage less with the strategic substitution.

Third, we examine the effect of between-analyst competition on the substitution effect we document. Analysts covering the same firm face peer competition (Hope and Su, 2021), which can diminish the incentive for strategic substitution. Higher competition means analysts may not be able to easily change the composition of their research if this can potentially negatively affect their standing with investors who can turn to other analysts to meet their information needs (Brown et al. 2015). Columns (v) and (vi) of Panel (D) in Table 7 divide firms into two groups based on the number of analysts following them. Firms in the *HighAF* group have above-median analyst coverage. We then interact the measure of analyst competition with *FLU*. The results show that the interaction coefficient is positive for short-term forecasts and negative for long-term forecasts, indicating that higher competition weakens the strategic substitution of short-term forecasts with long-term ones.

4.3.4 Flu and firm informational events

Analysts have the incentive to quickly update their forecasts following significant informational events as timeliness is one of the characteristics institutional investors value (Brown et al. 2015). We expect analysts to have a strong incentive to update their forecasts, including short-term forecasts, following major corporate events, which can moderate the effect we document. To test this prediction, Panel (E) of Table 7 examines analyst issuance of short-term and long-term EPS forecasts in weeks when a firm reports either management forecast or actual earnings. Both earnings announcements and management forecasts are major events that analysts are expected to respond to by revising their short-term and long-term forecasts. Therefore, any strategic substitution of forecasts should primarily occur on days when there are no earnings announcements or management forecasts. Columns (i) to (iv) of Panel (E) analyze the impact of earnings announcements and show that high flu seasons do not lead analysts to substitute forecasts during earnings announcement weeks, but rather in non-earnings announcement weeks. Similarly, Columns (v) to (viii) focus on management forecasts and find that strategic substitution by analysts occurs only in the weeks when no management forecasts are issued. This suggests that analysts are less likely to adjust their forecasting strategies during weeks with significant firm events. In summary, the cross-sectional evidence from Table 7 suggests that analysts consider factors such as investor information demand, employing brokerage house resources, reputational risk, and peer pressure when substituting short-term forecasts with long-term ones.

[Table 7 here]

4.4 Flu and career outcome

This section examines the effect that the substitution strategy has on analyst career outcomes. Mikhail et al. (1999) document that analysts are more likely to be terminated if they make less accurate earnings forecasts. Then analysts who switch to long-term forecasts would be able to avoid unfavorable career outcome. Table 8 reports the results for Equation (3). Columns (i) and (ii) report the results for analysts who relocated to a smaller brokerage house in the next 12-month window, whilst columns (i) and (ii) report analysts who move up to a larger broker. In general, issuing more short-term forecasts are appreciated as the coefficient on *CHSHORT* in column (i) is negatively significant, indicating less likelihood of moving down to a smaller broker. However, the coefficient on the interaction term *FLU×CHSHORT* is positively significant, suggesting issuing more short-term forecasts during the flu intensive time would increase the likelihood of unfavorable career moving. Column (ii) shows exactly the opposite, where we find negative significance on the interaction term of *FLU×CHLONG*, which indicates issuing more long-term forecasts during the flu intensive time reduce the probability of moving down. However, we do not find a similar pattern for the move-up cases in columns (iii) and (v) as all coefficients are insignificant at any conventional level.

[Table 8 here]

4.5 Generalizability of the results to non-EPS forecasts

Our tests focus on the supply of analyst EPS forecasts. However, it is plausible that analysts use a similar substitution when a publication of a low-quality non-EPS forecast may associate with negative reputational consequences. To test this prediction, we first focus on revenue forecasts. Revenue forecasts are available for almost the same population of firms as earnings estimates and are the most common forecasts on I/B/E/S after EPS (Bilinski 2024; Hand et al. 2022). Ertimur et al. (2011) document that analysts issue revenue forecasts to build reputation with investors. We expect that analysts will choose to substitute their short-term revenue forecasts with long-run estimates when they face production constraints due to flu. Columns (i) and (ii) in Panel (A) of Table 8 confirm this prediction. The effect is also economically significant – a one standard deviation increase in flu severity in a state associates with 1.7% less short-term forecasts and 2.1% more long-term estimates.

The second forecast we examine is the cash flow estimate. DeFond and Hung (2003, 73) report that analyst issue 'cash flows for firms where accounting, operating and financing characteristics suggest that cash flows are useful in interpreting earnings and assessing firm viability' and that issuance of cash flow estimates responds 'to market-based incentives to provide market participants with value-relevant information.' Call et al. (2013) report cash flow forecasts are useful to investors and Bilinski (2014) report that All-Star analysts and analysts at larger brokers – those with higher reputational capital – issue cash flow forecasts more frequently. Columns (iii) and (iv) in Panel (A) confirm the substitution effect for cash flow forecasts for analysts in high flu states.

The third forecast we examine is the return on equity (ROE) estimate. ROE directly measures investors' investment returns and ROE forecast would catch most of the attention from investors. The results from columns (v) and (vi) in Panel (A) supports our prediction that *FLU* is negatively (positively) associated with short-term (long-term) forecast issuance.

In addition, we present some measures that do not support analysts' strategic substitution, such as net debt forecast, fund from operations forecast, or enterprise value forecast. These forecasts are less likely to catch much attention from investors so that analysts have less incentive to conduct the strategic substitution. In the online appendix 3, we present the results by using all other forecast measures available from I/B/E/S. The results are largely consistent with our EPS forecasts, especially for the forecasts of income statement components (such as gross margin, EBITDA, EBIT, pre-tax profit, net income, and GAAP EPS). This confirms the prevalence of analysts' flu-induced strategic substitution across other financial item forecasting.

[Table 9 here]

V. Conclusion

This study examines how analysts respond to temporal constraints in research production due to flu. Flu constrains analysts short-term forecast quality and stock market recognizes the deterioration of short-term forecasts in the flu intensive time and reacts less strongly to analysts' short-term forecast revisions. We document that analysts strategically reduce the supply of short-term forecasts and increase the issuance of long-term EPS forecasts. This strategy helps analysts maintain the overall supply of research avoiding the costs of reduced supplied, such as lower visibility in the market (Brown et al. 2015), failing to cater to clients' informational needs (Groysberg et al. 2009), and reputational costs of issuing inaccurate forecasts (Hong et al., 2000). We also show how the effect varies cross-sectionally with analyst incentives to issue research and institutional demand for analyst forecasts. Lastly, we document evidence that strategic substitution during the flu intensive time facilitates analysts to avoid unfavorable career outcome.

Our research offers novel evidence on the actions analysts take when faced with temporal research constraints. The study goes beyond simply identifying changes in the properties of analyst forecasts, such as lower accuracy. This opens a new avenue for research to understand how analyst behavior changes in response to external shocks.

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Figure 1: Time trend of short-term vs long-term forecasts

This figure shows the time trend of the percentage of short-term versus long-term forecasts from 2001 to 2019.

Figure 2: Comparison of short-term vs long-term forecasts over flu severity

This figure demonstrates the percentage of short-term versus long-term forecasts over the decile of the weekly flu activities.

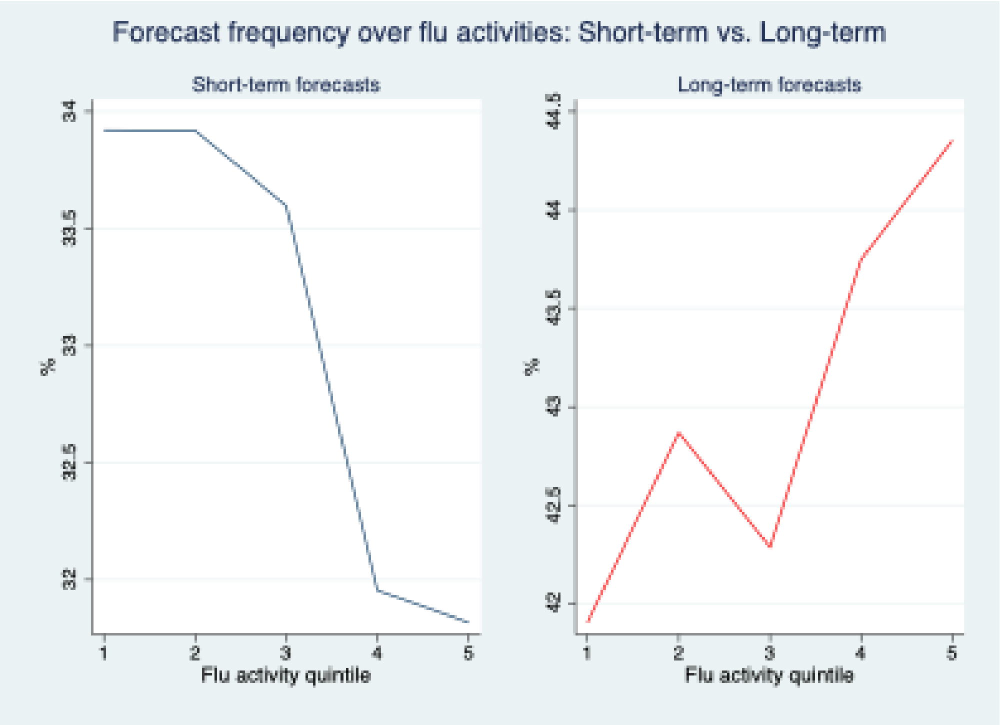
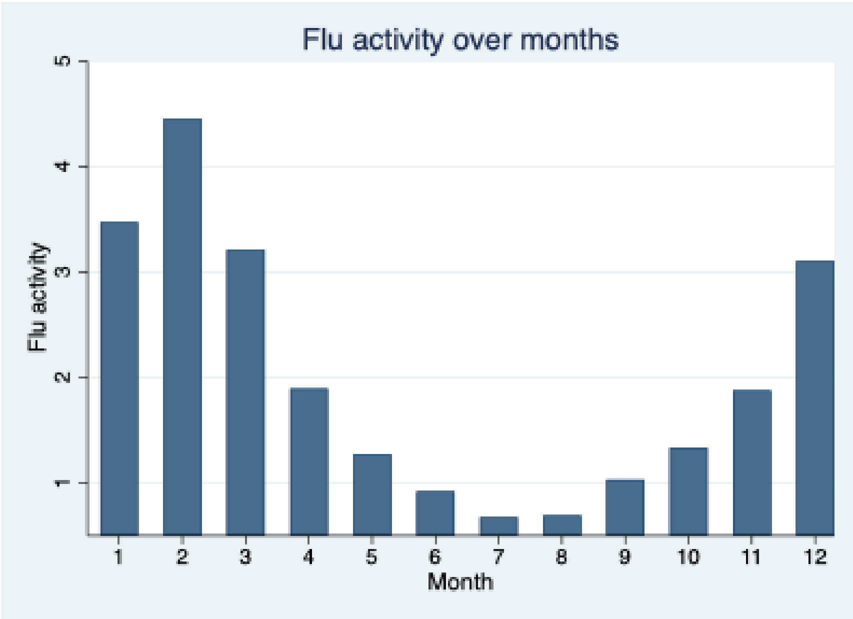


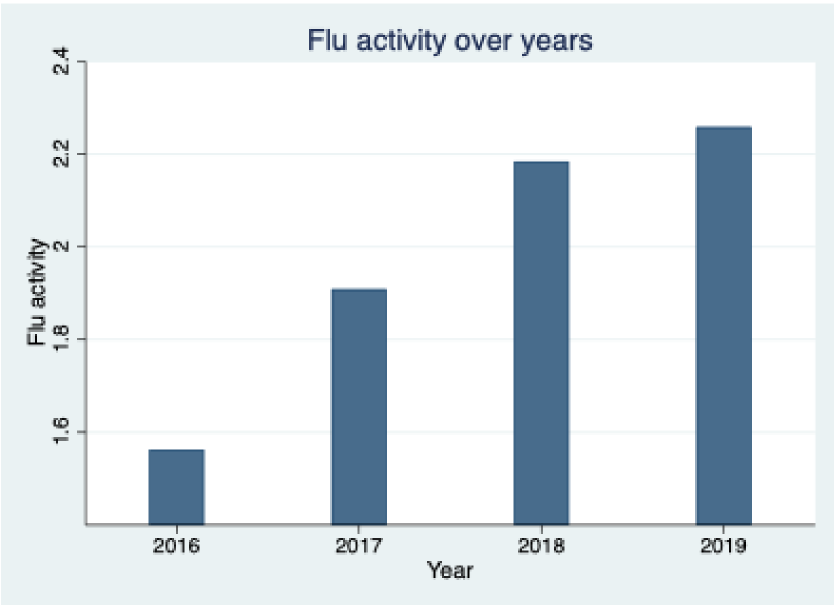
Figure 3: Flu activity over calendar months

This figure demonstrates the average flu activity over time. Panel (A) reports the flu activity over calendar months in a year. Panel (B) reports the flu activity over years.

Panel (A) Flu activity over calendar months



Panel (B) Flu activity over years



Appendix 1: Variable definitions

Panel (A): Dependent variables

Variable	Description	Source
NUMTOT_RAW	Total number of EPS forecasts with different forecast horizons issued by an analyst for a firm in a week.	I/B/E/S
NUMTOT	The natural logarithm form of *NUMTOT_RAW*.	I/B/E/S
NUMSHORT	The natural logarithm form of the numbers of short-term forecasts issued by an analyst for a firm in a week. A short-term forecast is defined as an EPS forecast with a forecasting period less than one year (FPI = 6, 7, 8, or A in I/B/E/S).	I/B/E/S
NUMLONG	The natural logarithm form of the numbers of long-term forecasts issued by an analyst for a firm in a week. A long-term forecast is defined as an EPS forecast with a forecasting period more than one year (FPI = 0, 2, 3, 4, 5, 10, C, D, E, F, G, N, O, P, Q, R, S, T, L, H, I, J, K, Y, Z, or X in I/B/E/S).	I/B/E/S
NUMONEYEAR	The natural logarithm form of the numbers of one-year-horizon forecasts issued by an analyst for a firm in a week. A one-year-horizon forecast is defined as an EPS forecast with a forecasting period equal to one year (FPI = 1, 9, B in I/B/E/S).	I/B/E/S
NUMSHORT_PC	The number of short-term EPS forecasts scaled by the total number of forecasts in the percentage form.	I/B/E/S
NUMLONG_PC	The number of long-term EPS forecasts scaled by the total number of forecasts in the percentage form.	I/B/E/S
NUMFONEYEAR_PC	The number of EPS forecasts with one-year-horizon scaled by the total number of forecasts in the percentage form.	I/B/E/S
FORERROR_SHORT	Forecast error of EPS with short-term horizon. Forecast error is defined by taking the absolute value of the difference between the EPS forecast and the actual value, scaled by the stock price at the beginning of the quarter.	I/B/E/S
FORERROR_LONG	Forecast error of EPS with long-term horizon. Forecast error is defined by taking the absolute value of the difference between the EPS forecast and the actual value, scaled by the stock price at the beginning of the quarter.	I/B/E/S
FORERROR_ONEYEAR	Forecast error of EPS with one-year horizon. Forecast error is defined by taking the absolute value of the difference between the EPS forecast and the actual value, scaled by the stock price at the beginning of the quarter.	I/B/E/S
RANGE_FORE	Forecast range, defined as the number of types of one-year-ahead forecasts issued by an analyst for a firm in a week in the natural logarithm form.	I/B/E/S
LFR_SHORT	Lead-follow ratio for the short-term forecasts. LFR is lead-follow ratio, defined as in Cooper et al. (2001) where we compare the number of days between a forecast and the forecasts by other analysts that precede and follow this forecast.	I/B/E/S
LFR_LONG	Lead-follow ratio for the long-term forecasts. LFR is lead-follow ratio, defined as in Cooper et al. (2001) where we compare the number of days between a forecast and the forecasts by other analysts that precede and follow this forecast.	I/B/E/S
LFR_ONEYEAR	Lead-follow ratio for the one-year horizon forecasts. LFR is lead-follow ratio, defined as in Cooper et al. (2001) where we compare the number of days between a forecast and the forecasts by other analysts that precede and follow this forecast.	I/B/E/S

Panel (B): Other variables

Variable	Description	Source
Flu measures		
FLU	The weekly state-level flu activity at analysts' states.	Centers for Disease Control
FLU_FIRM	The weekly state-level flu activity at firms' states.	Centers for Disease Control
Analyst control variables		
GEXP	Analysts' general experience, measured as the number of weeks from when the analyst issued her first forecast for any firm to the present.	I/B/E/S
FEXP	Analysts' firm-specific experience, measured as the number of weeks from when the analyst provided her first forecast for the specific firm to the present.	I/B/E/S
NUMIND	The number of two-digit SIC industries that the analyst covers.	COMPUSTAT
NUMFIRM	The number of companies that the analyst covers.	IB//E/S/
PASTACC	Relative accuracy score of an analyst in the previous year, which is calculated in line with Hong and Kubik (2003).	IB//E/S/
Firm control variables		
EAWEEKQ	Dummy variable with the value of one if the firm makes a quarterly earnings announcement, and zero otherwise.	I/B/E/S
EAWEEKA	Dummy variable with the value of one if the firm makes an annual earnings announcement, and zero otherwise.	I/B/E/S
MV	Market value of equity in the natural logarithm form.	COMPUSTAT
LEV	Financial leverage.	COMPUSTAT
ROA	Return on assets.	COMPUSTAT
MB	Market-to-book ratio.	COMPUSTAT
INTA	Intangible assets scaled by total assets.	COMPUSTAT
AF	Analyst following.	I/B/E/S
INST	Institutional investor ownership.	Thomson Reuters 13f
Partition variables		
HighBlock	Dummy variable with the value of one if a firm's block institutional investor ownership is higher than the median level, and zero otherwise.	Thomson Reuters 13f
HighTrans	Dummy variable with the value of one if a firm's transcient investor ownership is higher than the median level, and zero otherwise.	Brian Bushee Website
HighScore	Dummy variable with the value of one if an analyst past relative accuracy score is higher than 75th percentile, and zero otherwise.	I/B/E/S
LargeBro	Dummy variable with the value of one if an analyst's employing brokerage house has the number of analysts higher than the median level, and zero otherwise.	I/B/E/S
NewHired	Dummy variable with the value of one if an analyst has changed the job in the previous half a year, and zero otherwise	I/B/E/S
HighSCost	Dummy variable with the value of one if an analyst's switching cost (short-term to long-term forecasts) is high, and zero otherwise. Analyst's switching cost is defined as follows: (1) calculating the percentage of analysts' short-term forecasting numbers in the previous two months; (2) HighSCost equals to one if the previous short-term forecasting percentage in (1) is higher than median level, and zero if the previous short-term forecasting percentage less than the median level or analysts do not provide any forecasts in the previous 2 months.	I/B/E/S
TeamAn	Dummy variable with the value of one if the forecast is provided by a team, and zero otherwise. A team is defined as Kini et al. (2009) where an analyst ID covers more than 40 firms, and zero otherwise.	I/B/E/S
HighAF	Dummy variable with the value of one if a firm has analyst following higher than the median level, and zero otherwise.	I/B/E/S

Table 1: General data description

This table reports general description of analysts' locations in the sample and the average flu activities in each state over the sample period.

Panel (A): Analysts' locations

State	Number	Percent
New York	1,387	56.84
California	218	8.93
Texas	118	4.84
Illinois	113	4.63
Massachusetts	88	3.61
Ohio	55	2.25
Minnesota	50	2.05
Virginia	37	1.52
Connecticut	34	1.39
Oregon	34	1.39
Georgia	33	1.35
Tennessee	33	1.35
Maryland	30	1.23
Missouri	24	0.98
Louisiana	23	0.94
New Jersey	22	0.9
Colorado	21	0.86
Pennsylvania	19	0.78
Arkansas	11	0.45
Maine	9	0.37
Kentucky	7	0.29
North Carolina	6	0.25
Washington	6	0.25
South Carolina	5	0.2
Utah	4	0.16
Arizona	2	0.08
Nevada	2	0.08
Rhode Island	2	0.08
Wisconsin	2	0.08
Hawaii	1	0.04
Idaho	1	0.04
Indiana	1	0.04
Kansas	1	0.04
Michigan	1	0.04
Nebraska	1	0.04
South Dakota	1	0.04
Total	2,402	100

Panel (B): Average flu activity

State	Mean of Flu
Texas	3.86
Louisiana	3.36
Georgia	2.96
New Jersey	2.81
Hawaii	2.73
South Carolina	2.54
Arkansas	2.42
Virginia	2.38
Kentucky	2.35
Connecticut	2.28
Utah	2.27
New York	2.24
Kansas	2.22
Arizona	2.18
California	2.07
Tennessee	2.05
Minnesota	2.01
North Carolina	1.92
Indiana	1.87
Illinois	1.85
Missouri	1.80
Wisconsin	1.76
Maryland	1.75
Colorado	1.72
Pennsylvania	1.64
Idaho	1.63
South Dakota	1.48
Rhode Island	1.47
Oregon	1.42
Massachusetts	1.37
Ohio	1.14
Washington	0.98
Maine	0.95
Michigan	0.93
Nevada	0.91
Nebraska	0.53

Table 2: Descriptive statistics

This table reports the data description for all the tests in the paper. *NUMTOT_RAW* is the total number of EPS forecasts with different forecast horizons issued by an analyst for a firm in a week. *NUMTOT* is the natural logarithm form of *NUMTOT_RAW*. *NUMSHORT*, *NUMLONG*, and *NUMONEYEAR* are the natural logarithm form of the numbers of short-term, long-term, and one-year-horizon forecasts respectively issued by an analyst for a firm in a week. A short-term forecast is defined as an EPS forecast with a forecasting period less than one year (FPI = 6, 7, 8, or A in I/B/E/S). A long-term forecast is defined as an EPS forecast with a forecasting period more than one year (FPI = 0, 2, 3, 4, 5, 10, C, D, E, F, G, N, O, P, Q, R, S, T, L, H, I, J, K, Y, Z, or X in I/B/E/S). A one-year-horizon forecast is defined as an EPS forecast with forecasting periods equal to one year (FPI = 1, 9, B in I/B/E/S). *NUMSHORT_PC* is the number of short-term EPS forecasts scaled by the total number of forecasts in the percentage form. *NUMLONG_PC* is the number of long-term EPS forecasts scaled by the total number of forecasts in the percentage form. *NUMONEYEAR* is the number of EPS forecasts with one-year-horizon scaled by the total number of forecasts in the percentage form. *FORERROR* is forecast error, defined by taking the absolute value of the difference between the EPS forecast and the actual value, scaled by the stock price at the beginning of the quarter. *FORERROR_SHORT* (*_LONG* or *_ONEYEAR*) is the forecast error for short-term (long-term, or one-year-horizon) forecasts. *RANGE_FORE* is the forecast range, defined as the number of types of one-year-ahead forecasts issued by an analyst for a firm in a week in the natural logarithm form. *LFR* is lead-follow ratio, defined as in Cooper et al. (2001) where we compare the number of days between a forecast and the forecasts by other analysts that precede and follow this forecast. Specifically, we define *Leading Days* (*Following Days*) equals to the total number of days between an analyst's forecast for a firm for a fiscal period and the two most recent preceding (following) forecasts made by other analysts for the same firm and for the fiscal period. Then the lead-follow ratio (*LFR*) is *Leading Days* scaled by *Following Days*. *LFR_SHORT* (*_LONG* or *_ONEYEAR*) is the lead-follow ratio for short-term (long-term, or one-year-horizon) forecasts. *FLU* (*FLU_FIRM*) is the weekly state-level flu activity at analysts' (firms') states. The data is from the Centers for Disease Control (CDC) website. *GEXP* is analysts' general experience, measured as the number of weeks from when the analyst issued her first forecast for any firm to the present. *FEXP* is analysts' firm-specific experience, measured as the number of weeks from when the analyst provided her first forecast for the specific firm to the present. *NUMIND* is the number of two-digit SIC industries that the analyst covers. *NUMFIRM* is the number of companies that the analyst covers. *PASTACC* denotes the relative accuracy score of an analyst in the previous year, which is calculated in line with Hong and Kubik (2003). *EAWEEKQ* (*EAWEEKA*) is the dummy variable with the number of one if the firm makes a quarterly (annual) earnings announcement, and zero otherwise. *MV* represents the market value of equity in the natural logarithm form. *LEV* denotes the financial leverage. *INTA* indicates the percentage of intangible assets scaled by total assets. *MB* is the market-to-book ratio (measured by dividing the market value of equity by the book value of equity). *ROA* is return on assets. *INST* is the institutional investor ownership. *AF* is analyst following.

Variable	Obs	Mean	SD	p25	p50	p75
Panel (A): Dependent variables used in the analyses						
NUMTOT	385,997	1.903	0.510	1.609	1.946	2.303
NUMTOT_RAW	385,997	6.539	3.423	4.000	6.000	9.000
NUMSHORT	385,997	1.039	0.487	0.693	1.099	1.386
NUMLONG	385,997	1.208	0.608	0.693	1.099	1.609
NUMONEYEAR	385,997	0.833	0.347	0.693	1.099	1.099
NUMSHORT_PC	385,997	33.057	19.901	23.077	33.333	42.857
NUMLONG_PC	385,997	43.025	23.763	28.571	42.857	56.250
NUMFONEYEAR_PC	385,997	23.918	15.422	16.667	22.222	28.571
FORERROR_SHORT	755,605	0.609	1.480	0.063	0.181	0.492
FORERROR_LONG	887,493	3.064	13.567	0.232	0.721	2.209
FORERROR_ONEYEAR	500,954	1.175	3.054	0.104	0.312	0.896
RANGE_FORE	416,860	1.865	0.630	1.386	2.079	2.303
LFR_SHORT	356,431	1.785	4.952	0.000	0.289	1.400
LFR_LONG	567,879	2.888	7.560	0.043	0.536	2.000
LFR_ONEYEAR	292,706	2.659	7.364	0.000	0.400	1.778
CAR	814,481	0.045	4.883	-1.956	-0.010	1.914
MOVEDOWN	2,936	0.11	0.31	0.00	0.00	0.00
MOVEUP	2,936	0.09	0.28	0.00	0.00	0.00
Panel (B): Flu measure						
FLU	385,997	2.185	1.497	1.147	1.746	2.666
FLU_FIRM	331,372	2.220	1.993	0.959	1.634	2.784
Panel (C): Analyst controls						
GEXP	385,997	735.732	541.773	298.000	580.857	1120.143
FEXP	385,997	255.249	256.516	69.429	168.286	360.286
NUMIND	385,997	3.577	2.320	2.000	3.000	5.000
NUMFIRM	385,997	21.521	8.328	16.000	21.000	26.000
FREV	812,703	-0.031	0.415	-0.062	-0.006	0.037
CHLONG	2,936	-0.002	0.149	-0.068	0.000	0.062
CHSHORT	2,936	0.001	0.115	-0.048	0.000	0.054
PASTACC	385,997	50.770	6.043	47.863	50.663	53.531
Panel (D): Firm controls						
EAWEEKQ	385,997	0.467	0.499	0.000	0.000	1.000
EAWEEKA	385,997	0.119	0.324	0.000	0.000	0.000
MV	385,997	2.074	1.352	0.998	1.854	2.973
LEV	385,997	0.612	0.241	0.451	0.614	0.788
ROA	385,997	0.012	0.158	0.004	0.034	0.082
MB	385,997	4.090	8.793	1.438	2.539	4.841
INTA	385,997	0.199	0.224	0.013	0.105	0.341
AF	385,997	18.145	10.478	10.000	17.000	25.000
INST	385,997	0.777	0.240	0.675	0.835	0.939

Table 3: The effect of flu on market reaction to forecast revisions and on analyst forecast accuracy

This table presents the impact of flu activities on the market reaction to analysts forecast revisions for forecasts with different horizon (short-term [up to three quarters ahead], long-term [forecast horizon longer than one-year], and one-year-horizon), and on analyst forecast accuracy. Panel (A) presents the impact of flu activities on market reaction to analysts forecast revisions. The dependent variable is 3-day [0, 2] cumulative abnormal return. *FREV* is analysts' forecast revision, defined the defined as the difference between the forecast made by an analyst for the firm at the time and the previous forecast made by the same analyst for the same firm for the same fiscal period end, scaled by the absolute value of the previous forecast. Panel (B) reports the results for forecast accuracy. The dependent variable is forecast error (*FORERROR*), defined as the absolute value of the difference between the analyst earnings forecast and the actual value of earnings, scaled by the stock price at the beginning of the quarter. *FLU* is the weekly state-level flu activity at analysts' states. The data is from the Centers for Disease Control (CDC) website. All the regressions are clustered at the firm level and analyst level. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel (A) The flu effect on the market reaction to analyst forecast revisions

DepVar=CAR	Short	Long	OneYear	Short	Long	OneYear
	i	ii	iii	iv	v	vi
FLU * FREV	-0.052*	-0.013	-0.047	-0.061**	-0.019	-0.065**
	(0.028)	(0.033)	(0.032)	(0.027)	(0.035)	(0.031)
FREV	0.467***	0.796***	0.603***	0.268***	0.406***	0.358***
	(0.081)	(0.119)	(0.087)	(0.079)	(0.111)	(0.090)
FLU	0.136***	0.086***	0.125***	0.199***	0.139***	0.166***
	(0.026)	(0.025)	(0.024)	(0.032)	(0.029)	(0.029)
Observations	219384	339562	183282	214902	333989	108050
Adjusted R-squared	0.091	0.081	0.060	0.308	0.319	0.086
Analyst Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	No	No	No
FPI_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm_FE	Yes	Yes	Yes	No	No	No
Quarter_FE	Yes	Yes	Yes	No	No	No
Analyst_FE	Yes	Yes	Yes	Yes	Yes	Yes
FirmXQuarter_FE	No	No	No	Yes	Yes	Yes
StateXQuarter_FE	No	No	No	Yes	Yes	Yes

Panel (B): The effect of flu on analysts' forecast accuracy

	Short	Long	One-Year	Short	Long	One-Year
	0.609	3.064	1.175	0.609	3.064	1.175
	i	ii	iii	iv	v	vi
FLU	0.009***	-0.012	-0.007	0.007***	-0.012	-0.009
	(0.003)	(0.015)	(0.006)	(0.002)	(0.012)	(0.006)
Observations	755591	887464	500919	754701	886184	499169
Adjusted R2	0.564	0.417	0.566	0.686	0.460	0.714
Analyst Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	No	No	No
FPI_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm_FE	Yes	Yes	Yes	No	No	No
Qyear_FE	Yes	Yes	Yes	No	No	No
Analyst_FE	Yes	Yes	Yes	Yes	Yes	Yes
FirmXQyear_FE	No	No	No	Yes	Yes	Yes
StateXQyear_FE	No	No	No	Yes	Yes	Yes

Table 4: Flu and analyst research production

This table reports the results for analysts' strategic choice of issuing long-term or short-term forecasts with the seasonal flu severity. Panel (A) reports the total number of EPS forecasts with all different forecasting periods. The dependent variable is *NUMTOT_RAW* (or *NUMTOT*) is the total number of EPS forecasts with different forecast horizons issued by an analyst for a firm in a week (in the natural logarithm form). Panel (B) or Panel (C) reports the effect of flu on the number of short-term and long-term EPS forecasts provided by analysts in the percentage or in the natural logarithm form. *FLU* is the weekly state-level flu activity at analysts' states. The data is from the Centers for Disease Control (CDC) website. The dependent variable is the number of EPS forecast with short-term (long-term or one-year-horizon) forecasts in the percentage form (in the natural logarithm form). Standard errors clustered at analyst and firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel (A): Flu and the total supply of short- and long-run forecasts

DepVar	NUMTOT			NUMTOT_RAW		
	i	ii	iii	iv	v	vi
FLU	0.000	0.000	0.001	0.009	0.008	0.009
	(0.002)	(0.002)	(0.002)	(0.011)	(0.011)	(0.012)
Observations	385,964	382,778	382,778	385,964	382,778	382,778
Adjusted R2	0.355	0.369	0.372	0.396	0.410	0.413
Analyst Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	No	No	Yes	No	No
Firm_FE	Yes	No	No	Yes	No	No
Qyear_FE	Yes	No	No	Yes	No	No
Analyst_FE	Yes	Yes	Yes	Yes	Yes	Yes
FirmXQyear_FE	No	Yes	Yes	No	Yes	Yes
StateXQyear_FE	No	No	Yes	No	No	Yes

Panel (B): Flu and the number of short- and long-run EPS forecasts in percentage

DEPVAR	NUMSHORT_PC			NUMLONG_PC			NUMONEYEAR_PC		
	i	ii	iii	iv	v	vi	vii	viii	ix
FLU	-0.193***	-0.250***	-0.402***	0.446***	0.503***	0.745***	-0.253***	-0.253***	-0.343***
	(0.059)	(0.065)	(0.077)	(0.085)	(0.094)	(0.108)	(0.049)	(0.053)	(0.061)
Observations	385964	382778	382778	385964	382778	382778	385964	382778	382778
Adjusted R2	0.257	0.272	0.274	0.255	0.265	0.268	0.143	0.158	0.159
Analyst Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	No	No	Yes	No	No	Yes	No	No
Firm_FE	Yes	No	No	Yes	No	No	Yes	No	No
Qyear_FE	Yes	No	No	Yes	No	No	Yes	No	No
Analyst_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmXQyear_FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
StateXQyear_FE	No	No	Yes	No	No	Yes	No	No	Yes

Panel (C): Flu and the number of short- and long-run EPS forecasts in the natural logarithm form

DEPVAR	NUMSHORT	NUMLONG	NUMONEYEAR
	i	ii	iii
FLU	-0.006***	0.010***	-0.007***
	(0.001)	(0.002)	(0.001)
NUMTOT	0.729***	0.918***	0.523***
	(0.006)	(0.007)	(0.004)
Observations	382778	382778	382778
Adjusted R2	0.694	0.770	0.600
Analyst Controls	Yes	Yes	Yes
Analyst_FE	Yes	Yes	Yes
FirmXQyear_FE	Yes	Yes	Yes
StateXQyear _FE	Yes	Yes	Yes

Table 5: Reversal in the following weeks

This table reports the association of the number of forecasts in the following weeks with the flu severity. The dependent variables are the number of EPS forecasts with short-term (or long-term) forecasting periods scaled by total number of forecasts in the percentage form in the following one (two, or three, or four) week. *FLU* is the weekly state-level flu activity at analysts' states. Analyst-related control variables include: *GEXP* is analysts' general experience, measured as the number of weeks from when the analyst issued her first forecast for any firm to the present; *FEXP* is analysts' firm-specific experience, measured as the number of weeks from when the analyst provided her first forecast for the specific firm to the present; *NUMIND* is the number of two-digit SIC industries that the analyst covers; *NUMFIRM* is the number of companies that the analyst covers; *PASTACC* denotes the relative accuracy score of an analyst in the previous year, which is calculated in line with Hong and Kubik (2003). *EAWEEKQ* and *EAWEEKA* are also included. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

DepVar	in1wks		in2wks		in3wks		in4wks	
	Short	Long	Short	Long	Short	Long	Short	Long
	i	ii	iii	iv	v	vi	vii	viii
FLU	-0.149*	0.117	0.036	-0.366***	0.339***	-0.952***	0.656***	-1.438***
	(0.080)	(0.115)	(0.085)	(0.119)	(0.095)	(0.126)	(0.093)	(0.125)
Observations	382778	382778	382778	382778	382778	382778	382778	382778
Adjusted R-squared	0.262	0.250	0.264	0.250	0.265	0.250	0.265	0.251
Analyst Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
StateXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: The effect of influenza after control flu activities in firms' states.

This table reports the robustness tests to analysts' strategic choice of long-term versus short-term forecasts with the consideration of the flu severity of covered firms' location. The dependent variables are the number of EPS forecasts with short-term (long-term) forecasting periods scaled by total number of forecasts in the percentage form. *FLU* is the weekly state-level flu activity at analysts' states. Columns (i) and (ii) show the results with the addition of covered firms' state flu activity case. Columns (iii) and (vi) present the results of the regressions that only keeps analysts and firms are from different states. Columns (v) and (vi) report the results that only consider firms from states with low-flu severity. Low-flu severity states are defined as the states with weekly flu severity below the median level of all states' flu severity. Analyst-related control variables include: *GEXP* is analysts' general experience, measured as the number of weeks from when the analyst issued her first forecast for any firm to the present; *FEXP* is analysts' firm-specific experience, measured as the number of weeks from when the analyst provided her first forecast for the specific firm to the present; *NUMIND* is the number of two-digit SIC industries that the analyst covers; *NUMFIRM* is the number of companies that the analyst covers; *PASTACC* denotes the relative accuracy score of an analyst in the previous year, which is calculated in line with Hong and Kubik (2003). *EAWEEKQ* and *EAWEEKA* are also included. All the regressions are clustered at the firm level and the analyst level. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

DepVar	Adding firm HQ state flu level		Analysts in different states than firm HQ		Firms from low flu states only	
	Short	Long	Short	Long	Short	Long
	i	ii	iii	iv	v	vi
FLU	-0.227***	0.527***	-0.283***	0.628***	-0.338***	0.643***
	(0.086)	(0.121)	(0.084)	(0.114)	(0.102)	(0.134)
FLU_FIRM	-0.151**	0.237**				
	(0.073)	(0.101)				
Observations	328951	328951	313847	313847	166908	166908
Adjusted R2	0.599	0.704	0.599	0.702	0.282	0.280
Analyst Controls	Yes	Yes	Yes	Yes	Yes	Yes
Analyst_FE	Yes	Yes	Yes	Yes	Yes	Yes
FirmXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes
StateXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Cross-sectional analysis

This table reports the cross-sectional analysis. The dependent variable is the number of EPS forecasts with short-term (long-term) forecasting periods scaled by total number of forecasts in the percentage form. *FLU* is the weekly state-level flu activity at analysts' states. Analyst-related control variables include: *GEXP* is analysts' general experience, measured as the number of weeks from when the analyst issued her first forecast for any firm to the present; *FEXP* is analysts' firm-specific experience, measured as the number of weeks from when the analyst provided her first forecast for the specific firm to the present; *NUMIND* is the number of two-digit SIC industries that the analyst covers; *NUMFIRM* is the number of companies that the analyst covers; *PASTACC* denotes the relative accuracy score of an analyst in the previous year, which is calculated in line with Hong and Kubik (2003). *EAWEEKQ* and *EAWEEKA* are also included. Panel (A) reports the partition variable statistics. Panel (B) reports the moderating effect of institutional pressure. Panel (C) presents the moderating effect from analysts' employing brokerage houses. Panel (D) reports the moderating effect of analyst incentives to generate research. Panel (E) presents the results that consider firms' information events (earnings announcements and management forecast disclosure). All the regressions are clustered at the firm level and the analyst level. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel (A): Partition statistics

Variable	Obs.	mean
HighBlock	367,063	0.499
HighTrans	380,798	0.500
HighScore	385,997	0.292
LargeBro	341,725	0.484
NewHired	361,989	0.065
HighSCost	385,997	0.257
TeamAn	385,997	0.032
HighAF	385,997	0.482

Panel (B): The moderating effect of institutional pressure

	High Transient Investors		High Block Investors	
	Short	Long	Short	Long
	i	ii	iii	iv
FLU	-0.310***	0.621***	-0.312***	0.578***
	(0.086)	(0.123)	(0.087)	(0.125)
FLU * HighTrans	-0.177**	0.237**		
	(0.070)	(0.099)		
FLU * HighBlock			-0.176**	0.313***
			(0.071)	(0.102)
HighTrans	1.053***	-1.260***		
	(0.313)	(0.384)		
HighBlock			0.536*	-0.441
			(0.284)	(0.363)
Observations	377646	377646	364273	364273
Adjusted R2	0.274	0.268	0.274	0.268
Analyst Controls	Yes	Yes	Yes	Yes
Analyst_FE	Yes	Yes	Yes	Yes
FirmXQyear_FE	Yes	Yes	Yes	Yes
StateXQyear_FE	Yes	Yes	Yes	Yes

Panel (C) The moderating effect from analysts' employing brokerage houses

	Larger Brokerage House		Team Analysts		Newly Hired (<=26 wks)	
	Short	Long	Short	Long	Short	Long
	i	ii	iii	iv	v	vi
FLU	-0.578***	1.013***	-0.415***	0.763***	-0.437***	0.770***
	(0.094)	(0.136)	(0.077)	(0.108)	(0.082)	(0.115)
FLU * LargeBro	0.301***	-0.503***				
	(0.083)	(0.130)				
FLU * TeamAn			0.420**	-0.606*		
			(0.205)	(0.345)		
FLU * NewHired					0.226*	-0.513***
					(0.123)	(0.178)
LargeBro	-0.974**	1.188**				
	(0.410)	(0.555)				
TeamAn			-1.093*	1.240		
			(0.594)	(1.026)		
NewHired					0.091	0.458
					(0.432)	(0.546)
Observations	337984	337984	382778	382778	358505	358505
Adjusted R2	0.248	0.264	0.274	0.268	0.241	0.259
Analyst Controls	Yes	Yes	Yes	Yes	Yes	Yes
Analyst_FE	Yes	Yes	Yes	Yes	Yes	Yes
FirmXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes
StateXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel (D): The moderating effect of analyst incentives to generate research

	High Accuracy (>75pct)		High Switch Cost		High Analyst Following	
	Short	Long	Short	Long	Short	Long
	i	ii	iii	iv	v	vi
FLU	-0.361***	0.683***	-0.483***	0.925***	-0.483***	0.901***
	(0.082)	(0.114)	(0.081)	(0.109)	(0.085)	(0.121)
FLU * HighScore	-0.141*	0.214**				
	(0.076)	(0.107)				
FLU * HighSCost			0.268***	-0.551***		
			(0.069)	(0.090)		
FLU * HighAF					0.161**	-0.324***
					(0.082)	(0.114)
HighScore	0.337	-0.644*				
	(0.291)	(0.374)				
HighSCost			-1.102***	1.402***		
			(0.284)	(0.283)		
HighAF					-0.322	-0.246
					(0.313)	(0.385)
Observations	382778	382778	382778	382778	382778	382778
Adjusted R2	0.272	0.265	0.274	0.268	0.274	0.268
Analyst Controls	Yes	Yes	Yes	Yes	Yes	Yes
Analyst_FE	Yes	Yes	Yes	Yes	Yes	Yes
FirmXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes
StateXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel (E): The effect of information events

	EA_week	NonEA_week	EA_week	NonEA_week	MF_week	NonMF_week	MF_week	NonMF_week
	Short	Short	Long	Long	Short	Short	Long	Long
	i	ii	iii	iv	v	vi	vii	viii
FLU	0.128	-0.548***	-0.186	0.823***	0.082	-0.478***	0.118	0.699***
	(0.125)	(0.094)	(0.172)	(0.134)	(0.123)	(0.100)	(0.159)	(0.131)
Observations	173611	198292	173611	198292	121870	190132	121870	190132
Adjusted R2	0.369	0.253	0.393	0.233	0.382	0.259	0.391	0.243
Analyst Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
StateXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Career Outcome

This table reports the results for the career impact of analysts' strategic switching with the seasonal flu severity. The regression is on the analyst-month level, and only includes months when analysts relocate in the next 12 months. The dependent variable is a dummy variable *MOVEDOWN* (or *MOVEUP*) with the value of one if analyst relocated to a small (large) brokerage house in the next 12 months, and zero otherwise. A small (larger) brokerage house is defined as the number of unique analysts within a year for a brokerage house is less (more) than the median number of the analysts across all the brokerage house in I/B/E/S. *FLU* is the weekly state-level flu activity at analysts' states. The data is from the Centers for Disease Control (CDC) website. *CHSHORT* is the monthly percentage change of an analyst's short-term forecast issuance. *CHLONG* is the monthly percentage change of an analyst's long-term forecast issuance. Analyst-related control variables include: analysts' general experience (*GEXP*), the number of two-digit SIC industries that the analyst covers (*NUMIND*); the number of companies that the analyst covers (*NUMFIRM*), and the relative accuracy score of an analyst in the previous year (*PASTACC*), which is calculated in line with Hong and Kubik (2003). All the regressions are clustered at the analyst level. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

DepVar	MOVEDOWN		MOVEUP	
	i	ii	iii	iv
FLU	-0.490**	-0.482**	0.057	0.067
	(0.233)	(0.233)	(0.215)	(0.211)
FLU * CHSHORT	0.697**		0.364	
	(0.286)		(0.387)	
FLU * CHLONG		-0.321*		0.063
		(0.188)		(0.295)
CHSHORT	-1.864**		-0.193	
	(0.797)		(0.832)	
CHLONG		0.734		-0.442
		(0.502)		(0.762)
Observations	2922	2922	2849	2849
Pseudo R2	0.046	0.045	0.073	0.073
Analyst Controls	Yes	Yes	Yes	Yes
Month_FE	Yes	Yes	Yes	Yes

Table 9: Analysts' choice of long-/short-term forecasts in other type of financial items

This table reports analysts' strategic choice of issuing short-term or long-term forecasts in other types of financial items. The dependent variable is the number of revenue (cash flow or enterprise value) forecasts with short-term (long-term) forecasting periods scaled by total number of forecasts. *FLU* is the weekly state-level flu activity at analysts' states. The data is from the Centers for Disease Control (CDC) website. *GEXP* is analysts' general experience, measured as the number of weeks from when the analyst issued her first forecast for any firm to the present. *FEXP* is analysts' firm-specific experience, measured as the number of weeks from when the analyst provided her first forecast for the specific firm to the present. *NUMIND* is the number of two-digit SIC industries that the analyst covers. *NUMFIRM* is the number of companies that the analyst covers. *PASTACC* denotes the relative accuracy score of an analyst in the previous year, which is calculated in line with Hong and Kubik (2003). *EAweekQ* (*EAweekA*) is the dummy variable with the number of one if the firm makes a quarterly (annual) earnings announcement, and zero otherwise. Panel (A) presents some other financial items that also have the strategic shifting. Panel (B) shows some other financial items that do not have the strategic shifting. All the regressions are clustered at the firm level and the analyst level. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel (A): Financial items that also have the strategic shifting

	Revenue forecasts		Cashflow forecasts		Return on equity	
	Short	Long	Short	Long	Short	Long
	i	ii	iii	iv	v	vi
FLU	-0.357***	0.632***	-0.451***	0.945***	-0.198**	0.818***
	(0.082)	(0.105)	(0.163)	(0.233)	(0.089)	(0.160)
Observations	336285	336285	60509	60509	107757	107757
Adjusted R2	0.405	0.358	0.534	0.410	0.735	0.619
Analyst Controls	Yes	Yes	Yes	Yes	Yes	Yes
Analyst_FE	Yes	Yes	Yes	Yes	Yes	Yes
FirmXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes
StateXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel (B): Financial items that do not observe the strategic shifting

	Net Debt		Funds From Operations		Enterprise Value	
	Short	Long	Short	Long	Short	Long
	i	ii	iii	iv	v	vi
FLU	-0.064	0.613***	-0.019	0.959	0.006	0.597***
	(0.065)	(0.122)	(0.471)	(0.599)	(0.017)	(0.191)
Observations	80087	80087	11447	11447	50625	50625
Adjusted R2	0.692	0.452	0.161	0.23	0.736	0.586
Analyst Controls	Yes	Yes	Yes	Yes	Yes	Yes
Analyst_FE	Yes	Yes	Yes	Yes	Yes	Yes
FirmXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes
StateXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes

Online Appendix 1: Stock price reaction to forecast revision within each forecast horizon

Panel (A): Short-term forecast revisions

DepVar=CAR	1Q	2Q	3Q
	i	ii	iii
FLU	0.200***	0.221***	0.192***
	(0.037)	(0.035)	(0.034)
FREV	0.380***	0.194	0.422***
	(0.102)	(0.134)	(0.145)
FLU * FREV	-0.092**	-0.047	-0.105**
	(0.038)	(0.036)	(0.045)
Observations	64025	63432	57183
Adjusted R-squared	0.085	0.091	0.084
Analyst Controls	Yes	Yes	Yes
Analyst_FE	Yes	Yes	Yes
FirmXQyear_FE	Yes	Yes	Yes
StateXQyear_FE	Yes	Yes	Yes

Panel (B): Long-term forecast revisions

DepVar=CAR	2Y	3Y	4Y	5Q	6Q	7Q	8Q
	i	ii	iii	iv	v	vi	vii
FLU	0.165***	0.142***	0.087	0.103**	0.179***	0.204***	0.194***
	(0.031)	(0.049)	(0.089)	(0.040)	(0.049)	(0.051)	(0.067)
FREV	0.367***	0.661***	0.248	0.318*	0.346	0.767***	1.079**
	(0.136)	(0.206)	(0.702)	(0.175)	(0.222)	(0.294)	(0.469)
FLU * FREV	-0.020	-0.069	0.220	-0.019	0.003	-0.067	-0.089
	(0.047)	(0.064)	(0.195)	(0.054)	(0.068)	(0.085)	(0.114)
Observations	110153	57765	7629	37699	26411	18968	12578
Adjusted R-squared	0.092	0.102	0.142	0.094	0.092	0.087	0.125
Analyst Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
StateXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Online Appendix 2: Analysts' strategic switching for all other financial items

Panel (A): The remaining financial items still have the switching

	Gross Margin		EBITDA		EBIT		Pre-tax Profit		Net Income		GAAP EPS	
	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long
	iii	iv	v	vi	vii	viii	ix	x	xi	xii	xiii	xiv
FLU	-0.484***	0.756***	-0.365***	0.661***	-0.412***	0.793***	-0.387***	0.766***	-0.336***	0.685***	-0.350***	0.710***
	(0.144)	(0.198)	(0.085)	(0.116)	(0.072)	(0.098)	(0.068)	(0.102)	(0.070)	(0.098)	(0.087)	(0.123)
Observations	336285	336285	60509	60509	107757	107757	274642	274642	316614	316614	221036	221036
Adjusted R2	0.405	0.358	0.534	0.410	0.735	0.619	0.630	0.426	0.600	0.446	0.384	0.303
Analyst Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
StateXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel (B): The remaining financial items that do not have the switching

	Net Asset Value		Dividend Per Share		Return on Assets		EBITDA Per Share		Capital Expenditure	
	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long
	v	vi	ix	x	xi	xii	xiii	xiv	xv	xvi
FLU	-0.158	0.510***	-0.262	0.648**	-0.203	0.768***	-0.018	0.133	-0.121	0.700***
	(0.101)	(0.153)	(0.218)	(0.330)	(0.124)	(0.222)	(0.225)	(0.375)	(0.144)	(0.252)
Observations	89272	89272	53601	53601	66909	66909	18681	18681	87250	87250
Adjusted R2	0.703	0.502	0.398	0.266	0.679	0.369	0.637	0.451	0.463	0.304
Analyst Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
StateXQyear_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes