Decoding Momentum Spillover Effects

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Abstract

This paper studies the making of return predictability among economically linked firms. I characterize an asymmetric cross-firm tug-of-war: (1) high peer overnight returns are followed by elevated overnight returns for focal stocks, which fully reverse during intraday; (2) high peer intraday returns are followed by high intraday returns but minor overnight price reactions. This pattern accords with the story that individuals' persistent trading on salient information distorts opening prices, while slow-moving arbitrage by professional investors gradually corrects mispricing. Mutual fund and hedge fund flows exhibit distinct associations with the tug-of-war, supporting the hypothesis that heterogeneous demand drives the return predictability.

JEL Classification: G10, G12, G14

Keywords: Connected firms, Momentum spillover, Institutional investor, Retail investor

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I. Introduction

Stocks with economic connections (such as the customer-supplier relation) exhibit positive cross-autocorrelation in returns, also known as the momentum spillover effect. Starting with the early work by Moskowitz and Grinblatt (1999), Hou (2007), and Cohen and Frazzini (2008), a vast amount of research explores various settings of stock linkages, including, for example, upstream-downstream industries (Menzly and Ozbas, 2010), conglomerate firms (Cohen and Lou, 2012), alliance partners (Cao, Chordia, and Lin, 2016), text-based peers (Hoberg and Phillips, 2016, 2018), technological closeness (Lee, Sun, Wang, and Zhang, 2019), geographic links (Parsons, Sabbatucci, and Titman, 2020), and shared analyst coverage (Ali and Hirshleifer, 2020).[1]

Despite the literature's explosion in discovering new stock linkages, the proposed mechanisms remain largely coarse. The prevailing explanation typically describes a single-period scenario where investors overlook value-relevant information conveyed by peer stocks' returns, leading to an initial underreaction of prices. It remains unclear, however, how these shocks translate into prices, i.e., a characterization of *who* trades on *what*. This paper takes a different approach by linking return and trading behavior. I show that the interaction between professional and retail investors' trading generates both return *continuation* and *reversal* across stocks. Consequently, realized prices exhibit substantial fluctuations rather than smoothly converging to their fundamental values. As such, this study yields insights into how demand shocks contribute to

[1] A partial list of studies identifying economic linkages includes, among others, co-searches (Lee, Ma, and Wang, 2015), news co-mentions (Scherbina and Schlusche, 2015), shared directors (Burt, Hrdlicka, and Harford, 2020), labor market networks (Bali, Bae, Sharifkhani, and Zhao, 2021; Liu and Wu, 2025), cookie networks (Cheng, Lin, Lu, and Zhang, 2021), social ties (Peng, Titman, Yonac, and Zhou, 2022), competition links (Eisdorfer, Froot, Ozik, and Sadka, 2022), production complementarity (Lee, Shi, Sun, and Zhang, 2024), business networks (Breitung and Müller, 2025), and credit-rating comovement (Feng, Huo, Liu, Mao, and Xiang, 2025).

predictability among economically linked firms and elucidates the process of information diffusion in financial networks.

My starting point is to decompose price movements into the intraday component and the overnight component. This approach builds on the large literature showing that the clientele and information environment differ substantially between intraday and overnight periods (e.g., French and Roll (1986); Barclay and Hendershott (2003); Lou, Polk, and Skouras (2019); Boudoukh, Feldman, Kogan, and Richardson (2019), and Lou, Polk, and Skouras (2024)). The point-in-time and simple-to-measure construction allows me to dissect the generating process of momentum spillover effects while being applicable to various linkage settings.

Specifically, intraday returns are mainly driven by professional trades. Recent work such as Lou et al. (2019), Akbas, Boehmer, Jiang, and Koch (2021), and Bogousslavsky (2021) provides evidence that informed arbitrageurs operate during the daytime, whereas less sophisticated investors mainly trade at the market open; Lou et al. (2024) show that overnight clientele have features associated with households, while intraday clientele are typically characterized by institutions. Aligning with sophisticated investors' dominant role in intraday trading, French and Roll (1986) and Boudoukh et al. (2019) suggest that daytime order flows and intraday price fluctuations reflect private information to a larger extent than public news.

By contrast, overnight returns (price changes from the prior close to the next day's open) are driven by orders entered overnight and around market open, plausibly reflect retail investors' demand and attention-grabbing news. For example, overnight returns reveal the impact of salient and wide spread events that attract retail investor attention (Berkman, Koch, Tuttle, and Zhang, 2012; Engelberg, Sasseville, and Williams, 2012; Aboody, Even-Tov, Lehavy, and Trueman, 2018). Earnings and economic news are typically announced overnight (Jiang, Likitapiwat, and McInish, 2012), and retail participation in after-hours trading is heightened on days with scheduled corporate events (Cui, Gozluklu, and Haykir, 2025). Ahn, Fan, Noh, and Park (2024) identify a positive relationship between retail trading intensity and the inflation of opening prices. In addition, Boudoukh et al. (2019) show that public news plays a more crucial role in driving overnight return volatility than in driving intraday return volatility.

These facts suggest the feasibility of disentangling the channels of cross-stock return predictability by examining (1) the difference in the *predictive ability* of peer stocks' intraday and overnight returns; and (2) the *realization* of focal stocks' subsequent returns during the intraday and overnight periods. In this paper, I use the shared analyst coverage of Ali and Hirshleifer (2020) as my primary empirical setting; that is, two stocks are defined as connected peers if they share at least one common analyst coverage.[2]

I start by decomposing *peer* stocks' monthly returns into the intraday and overnight components and testing their predictive ability for focal stocks' future close-to-close returns. The connected-firm portfolio intraday return (CF Day) exhibits positive and significant predictive power, with the long-short strategy generating a value-weighted return of 0.72% and a seven-factor alpha of 1.01% per month. In sharp contrast, the connected-firm portfolio overnight return (CF Night) does not predict focal stocks' subsequent close-to-close price changes, and the average return of the CF Night strategy is small in magnitude (-0.14%). This pricing pattern is also confirmed in a series of Fama and MacBeth (1973) regressions.

I proceed by decomposing *focal* stocks' monthly returns to examine how strategy profits

[2]As shown in Ali and Hirshleifer (2020), shared analyst coverage captures a significant part of various cross-firm return predictability and provides a potentially unified measure of momentum spillover effects. In addition, the shared analyst sample also commits a sufficient coverage of the total stock universe, whereas other economic linkages are usually constrained by data availability. I also consider alternative connections such as industry links, text-based links, geographic links, technological links, and conglomerate firms as robustness checks and find the pattern remains similar.

materialize. While CF Night does not predict future close-to-close returns, higher peer stocks' overnight returns are associated with elevated opening prices for focal stocks, which fully reverse during the daytime period. Specifically, the CF Night strategy generates an overnight return of 1.40% and an intraday return of -1.43% per month. While I also find that CF Day positively (negatively) predicts future intraday (overnight) returns, its negative predictive ability for overnight returns is minor and unstable. The value-weighted CF Day strategy earns an intraday return of 0.96% per month, whereas the overnight return spread is only -0.31%. The correlation between CF Day and future overnight returns even becomes marginally positive after controlling for other variables in regressions.

In other words, an *asymmetric* tug-of-war (Lou et al., 2019) emerges in the context of cross-stock predictability: (1) an *inter-firm continuation* of overnight and intraday returns, where high CF Night (CF Day) is followed by high overnight (intraday) returns for the focal stock in the next month; (2) an *inter-firm daytime reversal* effect, evidenced by low subsequent monthly intraday returns after high CF Night; and (3) minor inter-firm overnight price reactions, as indicated by the weak relationship between CF Day and future monthly overnight returns. Figure 1 provides a graphical summary of the main findings.

[Insert Figure 1 about here]

This asymmetric cross-firm tug-of-war pattern reveals a deeper mechanism than what is suggested by the inattention story. Consider two types of investors (Lou et al., 2019, 2024), the intraday clientele (characterized by professional traders) and the overnight clientele (characterized by individuals). Since individuals are prone to over-extrapolation and tend to pursue glamour stocks (Lakonishok, Shleifer, and Vishny, 1994; Barber and Odean, 2008), their persistent trading distorts prices, generating the inter-firm continuation of overnight returns.[3] In other words, the focal stock's opening price continues to deviate from the fundamental value due to overnight clientele's persistent preferences.[4] Intraday investors, aware that overnight returns are sensitive to noise trading, disagree with the opening price. Consequently, intraday returns tend to reverse as the effective demand during the daytime does not align with the opening price. The opposing reactions of focal stocks' overnight and intraday returns thus lead to the absence of predictive power of CF Night for close-to-close returns.

For peer stocks' intraday price variations, investors face constraints in executing instantaneous arbitrage due to market friction and restrictions (Mitchell, Pedersen, and Pulvino, 2007; Duffie, 2010). Daytime investors trade with a delay, leading to the inter-firm continuation of intraday returns. Anomaly returns result as focal stocks' prices are gradually corrected by arbitrageurs. In contrast, overnight investors do not significantly trade on peer stocks' intraday returns due to the greater salience of overnight news (Berkman et al., 2012; Engelberg et al., 2012). Therefore, the focal stock's overnight return does not react strongly to peers' intraday returns. The asymmetric responses of focal stocks' overnight and intraday returns thus contribute to the positive predictive ability of CF Day for close-to-close returns.

I conduct a series of tests to validate this mechanism. First, I show that CF Day positively and significantly forecasts future changes in the breadth of institutional investor ownership (Chen, Hong, and Stein, 2002; Lehavy and Sloan, 2008) and future changes in institutional holding.

[3]Indeed, previous research (e.g., Barber, Odean, and Zhu (2008); Aboody et al. (2018); McLean, Pontiff, and Reilly (2025); Dong and Yang (2023); and Laarits and Sammon (2025)) finds that retail investors' trading is highly persistent, and that their trading preferences are more persistent than those of institutions (Barber et al., 2008).

[4]To clarify, the argument here does not posit that retail investors exactly observe or understand economic links. Rather, prior work (e.g., Goetzmann and Kumar (2008) and Balasubramaniam, Campbell, Ramadorai, and Ranish (2023)) shows that individuals tend to hold underdiversified portfolios. As a result, the peer set salient to retail investors likely overlaps with economically connected firms. Section II.B provides examples and additional discussion.

Crucially, peer stocks' overnight returns are unrelated to institutional investors' subsequent recognition and trading. This result supports the story that the price correction from professional traders' behavior leads to the positive predictive ability of peer stocks' intraday returns, while the insufficiency in the effective demand in response to peer stocks' overnight returns contributes to the cross-stock daytime reversals.

Second, the magnitude of CF Night positively and significantly correlates with subsequent retail attention (Da, Engelberg, and Gao, 2011). On the contrary, CF Day does not attract retail attention. CF Night also positively predicts retail investors' net purchase, whereas the effect of CF Day is minor. This finding aligns with prior work that overnight news attracts attention, and the trading preference of retail investors is persistent. In contrast, peer stocks' intraday price movements are largely underrated by individuals. As a result, overnight returns tend to continue across stocks, while the reaction of future overnight returns to peer stocks' intraday returns is marginal as individuals' attention is drawn more to overnight price variations.

Third, I compare variations in different types of order imbalance. I show that CF Night positively predicts retail order imbalance, whereas CF Day does not. In sharp contrast, the predictive ability of peer stocks' intraday and overnight returns undergoes a notable shift for *total* order imbalance, where professional traders are more likely to dominate. Specifically, CF Day positively and significantly predicts the focal stock's total order imbalance, while CF Night displays a slightly negative correlation with subsequent total order imbalance. This finding provides further evidence of the distinction between retail and professional trades in response to peer stocks' overnight and intraday returns.

Fourth, I examine the time variation in the cross-firm tug-of-war by analyzing flows to mutual funds and hedge funds (Akbas, Armstrong, Sorescu, and Subrahmanyam, 2015). The intuition behind this test is that an influx of "dumb money" would exacerbate price distortions, while an increase in "smart money" facilitates price correction. Consistently, I show that aggregate mutual fund flows are associated with stronger overnight return continuation and daytime reversals, whereas hedge fund flows imply a more pronounced continuation of intraday returns.

What drives the observed discrepancy between professional and retail investors' trading? Differences in the information content between peer stocks' intraday and overnight returns shed light on this question. It turns out that CF Day is positively associated with the future profitability of focal stocks, while CF Night exhibits a negative correlation with subsequent profitability. Moreover, CF Night is positively related to *growth* in total assets, sales, and revenues, whereas the relationship between CF Day and fundamental growth is minor. This pattern is consistent with the tendency of retail investors to be drawn to salient signals and to chase glamour stocks. Overall, these findings support my earlier results on trading metrics, suggesting that persistent speculative trading by individuals distorts opening prices, while slow-moving arbitrage by professional investors gradually corrects mispricing.

Finally, I explore intraday patterns of cross-firm tug-of-war. Bogousslavsky (2021) suggests that institutions primarily trade on mispricing early in the day, and they tend to unwind positions before market close to mitigate the costs and risks associated with overnight periods. Consequently, anomaly returns typically accrue throughout the day but get attenuated at the end of the day. Consistent with this channel, the positive (negative) intraday returns of the CF Day (CF Night) strategy are concentrated in the early trading sessions and reverse during the last 15-minute interval before market close. I conduct a battery of additional tests to evaluate the robustness of the main results and the mechanism.

This paper contributes to the existing literature that explores the explanations for cross-firm return predictability. Building on the inattention channel, Huang, Lin, and Xiang (2021) highlight the role of anchoring bias (George and Hwang, 2004), whereas Huang, Lee, Song, and Xiang (2022) focus on information discreteness (Da, Gurun, and Warachka, 2014). Burt and Hrdlicka (2021) show that the return predictability of economically linked firms could also come from their commonality in momentum. Different from these studies, I focus on the role of investor composition and the driving force underlying the *realization* of anomaly returns. The coexistence of cross-momentum and reversal is an important complement to existing explanations, which predominantly focus on variations in anomaly signals without systematically examining investors' trading behavior.[5]

I also complement growing work on asset pricing implications of the overnight-intraday price dynamics.[6] The pioneering work by Lou et al. (2019) propose a clientele perspective on the tug-of-war predictability of overnight and intraday returns. Follow-up studies include the pricing effect of tug-of-war intensity (Akbas et al., 2021), heterogeneous liquidity providers (Lu, Malliaris, and Qin, 2023), and equity premium forecasts (Lou et al., 2024). Hendershott, Livdan, and Rösch (2020) study the capital market line with beta estimated during different time periods, while Bogousslavsky (2021) finds that mispricing gradually corrects over the day but worsens at the end of the day. Barardehi, Bogousslavsky, and Muravyev (2023) propose to use the overnight/intraday decomposition to distinguish between public and private information flows.

This paper differs from prior research in two key aspects: (1) I focus on *cross-stock* return predictability rather than own-autocorrelations, and (2) I decompose and study *both* the formation

[5]My findings suggest that the generating process of these predictability patterns is more complex than a single-period inattention story, which shares the perspective of Burt and Hrdlicka (2021). Understanding the making of these anomaly patterns is crucial for risk management, as an increasing amount of capital has been allocated to momentum-type trading strategies.

[6]Earlier work includes, for example, Barclay, Litzenberger, and Warner (1990); Stoll and Whaley (1990); Jones, Kaul, and Lipson (1994); Barclay and Hendershott (2003); and Heston, Korajczyk, and Sadka (2010).

and holding period returns. Importantly, I document an asymmetric inter-firm tug-of-war pattern that shows how demand shocks from different clientele create return spillover in economic links. The findings suggest that investor heterogeneity and demand variations, beyond inattentiveness, play a significant role in generating the intricate cross-predictability patterns in stock returns.

The rest of the paper is organized as follows. Section II describes the data sources and variable constructions. Section III presents the results of decomposing peer stocks' returns. Section IV further studies the intraday and overnight returns of focal stocks. Section V examines the mechanisms and provides additional robustness tests. Section VI concludes.

II. Data and variables

The main sample used in this paper covers non-financial common stocks (share codes 10 or 11) listed on NYSE, NASDAQ, and AMEX. Stock returns and price data are obtained from CRSP, and accounting information is from COMPUSTAT. I exclude stocks with a share price below $5 at the end of each month and require stocks to have at least 10 trading day records during the month. Constrained by the availability of opening prices data, the sample period is from July 1992 to December 2021.[7]

The analyst forecast data come from the unadjusted detail history file of the Institutional Brokers Estimate System (IBES). I obtain quarterly data on institutional investor (13F) holdings and the number of institutional investors from ThomsonReuters. Data on retail trades are acquired from the WRDS - TAQ Millisecond Tools database. The time series of monthly risk-free rates and Fama-French factor returns are downloaded from Ken French's website.

[7]The CRSP opening price data are available for stocks listed on NYSE, NASDAQ, and AMEX only beginning June 15, 1992. Therefore, my sample starts from July 1992 in order to calculate monthly intraday and overnight returns.

A. Intraday and overnight returns

Following prior studies, for each firm i, the intraday return ($r_{i,s}^{Day}$) and overnight return ($r_{i,s}^{Night}$) on day s are defined as

$$r_{i,s}^{Day} = \frac{P_{i,s}^{close} - P_{i,s}^{open}}{P_{i,s}^{open}}, \quad r_{i,s}^{Night} = \frac{1 + r_{i,s}^{close-to-close}}{1 + r_{i,s}^{Day}} - 1, \tag{1}$$

in which the daily close-to-close return, $r_{i,s}^{close-to-close}$, is the holding period return adjusted for corporate events such as dividend distributions or stock splits. Then, I calculate monthly intraday and overnight returns by cumulating daily returns over each month:

$$r_{i,t}^{Day} = \Pi_{s=1}^{S_{i,t}}(1 + r_{i,s}^{Day}) - 1, \quad r_{i,t}^{Night} = \Pi_{s=1}^{S_{i,t}}(1 + r_{i,s}^{Night}) - 1, \tag{2}$$

where $S_{i,t}$ is the number of trading days of stock i in month t.

B. Shared analyst coverage signals

I follow the same procedure as Ali and Hirshleifer (2020) in constructing the shared analyst coverage. Each month, two stocks are defined as connected if at least one analyst has issued FY1 or FY2 earnings forecasts for both stocks over the previous 12 months. Then, the connected-firm portfolio return (CF RET) of focal firm i in month t is calculated by

$$CF\ RET_{i,t} = \frac{1}{\sum_{j=1}^{N_{i,t}} n_{i,j}} \sum_{j=1}^{N_{i,t}} n_{i,j} Ret_{j,t}, \tag{3}$$

where $n_{i,j}$ is the number of shared analysts between focal firm i and peer firm j, $N_{i,t}$ is the total number of peer stocks (j) connected to each focal firm (i) as of the formation date, and $Ret_{j,t}$ is the total return of peer stock j during month t. Analogously, I define the connected-firm portfolio intraday return (CF Day) and connected-firm portfolio overnight return (CF Night), respectively, as the following:

$$(4)\ \ CF\ Day_{i,t} = \frac{1}{\sum_{j=1}^{N_{i,t}} n_{i,j}} \sum_{j=1}^{N_{i,t}} n_{i,j}(1+r_{j,t}^{Day}), \quad CF\ Night_{i,t} = \frac{1}{\sum_{j=1}^{N_{i,t}} n_{i,j}} \sum_{j=1}^{N_{i,t}} n_{i,j}(1+r_{j,t}^{Night}),$$

in which $r_{j,t}^{Day}$ and $r_{j,t}^{Night}$ are the cumulative intraday return and cumulative overnight return of peer firm j during month t, respectively, as defined in equation (2).

While my main analysis leverages the shared analyst coverage setting, this paper does not assume that investors, particularly retail investors, trade specifically along analyst connections. A large literature shows that retail investors hold underdiversified portfolios (Goetzmann and Kumar, 2008; Balasubramaniam et al., 2023) and, even without recognizing it, tend to trade stocks that share economic links. For example, retail investors exhibit positive-feedback trading within industries (Jame and Tong, 2014), purchase stocks with similar characteristics due to categorical thinking (Kumar, 2009) or personal experiences (Huang, 2019), display preferences for local stocks (Seasholes and Zhu, 2010), and follow analysts' recommendations in their trades (McLean, Pontiff, and Reilly, 2024). Since shared analyst coverage unifies many forms of economic connections (Ali and Hirshleifer, 2020), it provides a parsimonious proxy for the set of firms investors are likely to track. For robustness, I also consider several alternative definitions of economic links.

C. Other lead-lag settings and control variables

In addition to the shared analyst coverage, I examine five alternative economic linkage settings, including industry links, text-based links, geographic links, technological links, and conglomerate firms. For industry links, I use the Fama-French 49 industry classification and the three-digit SIC codes industry classification. For text-based links, I use the text-based industry classification developed by Hoberg and Phillips (2010, 2016). For geographic links, I use each firm's headquarters location based on the ZIP code in COMPUSTAT. The geographic peer firms are identified using the first three-digit ZIP codes. For technological links, I use the patent data provided by Kogan, Papanikolaou, Seru, and Stoffman (2017) and define technology-linked firms following the methodology of Lee et al. (2019). For conglomerate firms, I rely on firms' industry segment data extracted from COMPUSTAT segment files and calculate pseudo-conglomerate portfolio returns for each conglomerate firm, following Cohen and Lou (2012). For the sake of brevity, I leave the details of data and signal constructions in Appendix B.

In baseline regressions, I control for each stock's past performance, including the 1-month return and the 12-month return (skipping the most recent month). Second, I control for firm size, calculated as the logarithm of market capitalization, and the log of the book-to-market ratio. Finally, I control for idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang, 2006) and illiquidity. Idiosyncratic volatility is calculated using one-month daily returns relative to the Fama-French three-factor model; illiquidity is measured using the average daily ratio of the absolute return over dollar trading volume in the past month (Amihud, 2002).

D. Institutional and retail investor variables

For institutional investor-related variables, I measure institutional recognition by calculating quarterly changes in the breadth of institutional investor ownership (ΔBD), as in Chen et al. (2002) and Lehavy and Sloan (2008). Specifically, ΔBD measures the change in the proportion of 13F filers holding a stock:

$$\Delta \text{BD}_{i,q} = \frac{Num_{i,q} - Num_{i,q-1}}{TotalNum_{q-1}}, \tag{5}$$

where $Num_{i,q}$ and $Num_{i,q-1}$ are the number of 13F filers holding stock i during quarter q and quarter $q-1$, respectively; $TotalNum_{q-1}$ is the total number of 13F filers in quarter $q-1$. I also measure institutional investors' trading (ΔINST) using quarterly changes in institutional ownership (Edelen, Ince, and Kadlec, 2016).[8]

For retail investor-related variables, I use Google search volume to capture retail investor attention (Da et al., 2011). Specifically, I define abnormal Google search volume as the log difference between the Google search volume in the current month and the average of Google search volume over the past year. I also obtain daily retail trading volume from the WRDS - TAQ Millisecond Tools database, in which retail trades are identified based on the Boehmer, Jones, Zhang, and Zhang (2021) algorithm. Then, I calculate daily retail trading as retail buys volume minus retail sells volume, scaled by shares outstanding (McLean et al., 2025). For each stock, the monthly net purchase of retail investors is computed by aggregating daily retail trading within the month.[9]

[8] Following Nagel (2005), institutional ownership below 0.01% and above 99.99% are replaced with 0.01% and 99.99%, respectively.

[9] As suggested by McLean et al. (2025), this construction facilitates a relatively direct comparison with the trading metrics related to institutional investors.

E. Order imbalance and fund flows

Order imbalance is calculated based on the number of trades, trading volume, and dollar value. Trade imbalance is calculated by the difference in the number of buys and number of sells divided by the total number of buys and sells. Volume imbalance is shares of buy trades minus shares of sell trades divided by the total volume of buys and sells. Value imbalance is the difference in the dollar value of buys and the dollar value of sells divided by the total dollar value of buys and sells. Then, for each stock, the monthly order imbalance is computed by averaging the daily order imbalance within the month. Retail order imbalance is constructed analogously using the Boehmer et al. (2021) method.

I follow the procedure of Akbas et al. (2015) to calculate flows to mutual funds (MFFLOW) and flows to hedge funds (HFFLOW). Specifically, the monthly aggregate fund flows are calculated as:

$$\begin{aligned} MFFLOW_t &= \frac{\sum_{i=1}^{N}\left[TNA_{i,t} - TNA_{i,t-1}(1 + MRET_{i,t})\right]}{\sum_{i=1}^{N} TNA_{i,t-1}}, \\ HFFLOW_t &= \frac{\sum_{i=1}^{N}\left[TNA_{i,t} - TNA_{i,t-1}(1 + HRET_{i,t})\right]}{\sum_{i=1}^{N} TNA_{i,t-1}}, \end{aligned} \tag{6}$$

where $TNA_{i,t}$ is the total net assets of fund i, and $MRET_{i,t}$ and $HRET_{i,t}$ denote the net-of-fee returns of a mutual fund and a hedge fund, respectively. Mutual fund data are obtained from the CRSP Survivor-Bias-Free US Mutual Fund Database, while hedge fund data are obtained from the Lipper TASS database.

F. Summary statistics

Table 1 reports summary statistics for the main variables used in my analysis. Panel A reproduces the post-1992 statistics for shared analyst coverage. On average, each firm is connected to 77 other stocks through common analyst coverage, with more than half of the firms having analyst-linked stocks of at least 68. Over the period from 1992 to 2021, stocks with shared analyst coverage represent 82% of the total number of stocks and account for 98% of the total stock market capitalization. Regarding the returns of peer firms, the distributions of signals using close-to-close return (CF RET), intraday return (CF Day), and overnight return (CF Night) are comparable. Overall, CF Night exhibits slightly higher values compared to CF RET and CF Day while also displaying a smaller standard deviation. Similarly, Panel B shows that the focal stock's intraday returns are more volatile than its overnight returns.

Panel C and Panel D present variables related to investor activity and order imbalance. Institutional recognition (ΔBD) and institutional trading (ΔINST) have positive means (Lehavy and Sloan, 2008; McLean et al., 2025), while the average net purchase by retail investors is close to zero (McLean et al., 2025). Order imbalance is negative on average, particularly for retail order imbalance. This pattern is consistent with the evidence documented in previous studies (Boehmer et al., 2021; Charles, 2024). Panel E reports flows to mutual funds and hedge funds. In line with Akbas et al. (2015), average hedge fund flows exceed mutual fund flows, and both MFFLOW and HFFLOW exhibit substantial time-series variation.

[Insert Table 1 about here]

III. Lead-lag relation from decomposing peer stock returns

A. Portfolios based on peers' intraday and overnight returns

This section examines the predictive ability of peer stocks' intraday and overnight returns. Figure 2 presents the baseline results graphically. Each month, stocks are separately sorted into quintile portfolios based on CF RET, CF Day, or CF Night. Then, value-weighted and equal-weighted portfolios are formed and held for one month. Table 2 reports the average returns and alphas of portfolios formed by different return signals. First, it confirms that shared analyst coverage continues to deliver significant returns in the post-1992 sample period. Panel A shows that the long-short strategy based on value-weighted portfolios generates a four-factor alpha of 76 basis points (t=2.62) and a seven-factor alpha of 93 bps (t=3.89) per month. The result based on equal-weighted returns is stronger. For instance, Panel B shows that the CF RET strategy earns a return of 1.53% per month during the 1992 to 2021 period, with a t-statistic of 4.50. The risk-adjusted alphas are larger than 1.68% and highly significant.

[Insert Figure 2 about here]

[Insert Table 2 about here]

Regarding the intraday component of peer stocks' returns, I find that CF Day positively and significantly predicts focal stocks' future returns. The long-short CF Day strategy earns a higher and more robust return than the 24-hour signal (CF RET) under the value-weighting scheme. For instance, the Carhart alpha of the CF Day strategy in my sample period is 0.95% (t=3.53), surpassing the return of the CF RET strategy by 19 bps. For equal-weighted returns, strategies based on CF Day and CF RET exhibit a similar performance and attain statistical significance at the 1% level.

The relationship between CF Night and the future returns of focal stocks differs sharply. In particular, the long-short strategy based on CF Night fails to generate positive profits. If any, the average monthly return is negative and statistically insignificant, regardless of whether value weighting or equal weighting is applied. Moreover, CF Night even generates a significantly negative return after adjusting for the Carhart factors. The four-factor alpha of the CF Night strategy is -0.44% (t=-1.85) for value-weighted portfolios and -0.53% (t=-2.46) for equal-weighted portfolios.[10] The seven-factor alpha exhibits a small magnitude, with t-statistics less than 1 in absolute value.

As a robustness test, Figure 3 presents portfolio returns under alternative inter-firm connection specifications. Consistent with the shared analyst coverage setting, cross-firm return predictability emerges only when the signal is based on intraday returns. For instance, when firms are linked by the Fama-French 49 industry classification (INDFF), the long-short strategy constructed with INDFF Day earns an average close-to-close return of 68 basis points per month (t=3.68), whereas the strategy return based on INDFF Night is -0.002% (t=-0.01). Similar patterns obtain across the other linkage specifications.

[Insert Figure 3 about here]

[10]The negative alpha of the CF Night strategy is suggestive of a potential short-term overreaction effect. Previous studies such as Berkman et al. (2012) and Engelberg et al. (2012) find that retail investors are indeed prone to overreact to overnight news.

B. Fama-MacBeth regressions

Table 3 reports the Fama-MacBeth regression results of shared analyst coverage signals. In particular, I control for the focal stock's own past monthly return using two specifications: I use the focal stock's monthly close-to-close return (Ret CC) in columns (3) and (4), while I use the focal stock's monthly intraday return (Ret Day) and monthly overnight return (Ret Night) in columns (5) and (6). Consistent with the portfolio analysis, CF RET is positively associated with future returns. The average slope is above 0.50 and highly significant.

The predictive ability of CF Day remains robust after controlling for the focal stock's own past intraday and overnight returns. Column (6) shows that a one-standard-deviation increase in CF Day implies an increase in focal stocks' future returns of 0.57% (t=6.36). By contrast, CF Night is unrelated to focal stocks' returns in the next month. The magnitude of the estimated coefficient on CF Night is minor and insignificant across all specifications.

[Insert Table 3 about here]

It's worth noting that the findings in this section do not lead to a conclusion that the pricing of peer stocks' overnight returns is more "correct" nor that intraday returns are more informative about fundamentals. I will show that the underlying mechanism is more complicated than a single-period narrative when it comes to cross-predictability. To elucidate this complexity, the analysis proceeds as follows: First, I decompose focal stocks' subsequent returns to examine the realization process of predictability. Second, I investigate the demand and impact of professional and retail investors to characterize the dynamic formation of momentum spillovers. Finally, I examine the information content of peer stocks' intraday and overnight returns to further substantiate the earlier findings. These tests provide a more comprehensive understanding of the intricate predictability patterns.

IV. The cross-firm tug-of-war

This section examines when the strategy profit materializes to further investigate the source of cross-predictability. In particular, I separately track focal stocks' future intraday and overnight returns based on peer stocks' past price changes. I first construct one-sort portfolios to study the return performance during the two periods. Then, I conduct Fama-MacBeth regressions to control for other variables that potentially predict subsequent daytime and overnight performance. In particular, I control for focal stocks' own past intraday and overnight returns (Lou et al., 2019) to assess the robustness of my findings. Finally, I summarize the results and discuss the decomposition of the cross-firm return predictability.

A. Portfolio analysis

To examine the predictive ability of return signals from peer stocks for focal stocks' future intraday and overnight performance, I begin by constructing one-sort portfolios. Specifically, stocks are sorted into five groups based on CF RET, CF Day, and CF Night, respectively. I then track future one-month intraday and overnight returns of the quintile portfolios. Average returns and alphas of the long-short strategy are also computed for different return types.

Figure 4 illustrates the main findings discussed in this section. More detailed results are presented in Table 4. First, I find that the profitability of the CF RET strategy is mainly generated intraday. For value-weighted portfolios, the intraday return spread between the top and bottom

CF RET quintiles is 49 bps (t=2.10), whereas the overnight return spread is only 0.09% and insignificant. However, the relationship between CF RET and future intraday/overnight returns is not monotonic, despite the return difference between extreme quintiles being significant.

[Insert Figure 4 about here]

[Insert Table 4 about here]

My focus is on the cross-stock interaction between intraday and overnight returns. First, there is a tendency of *continuation* for overnight and intraday returns among connected firms: the past overnight (intraday) returns of peer stocks positively forecast the subsequent overnight (intraday) returns of focal stocks. For value-weighted portfolios, Panel A of Table 4 shows that the long-short strategy based on CF Night (CF Day) yields a monthly overnight (intraday) return of 1.40% (0.96%) with a t-statistic of 4.46 (3.97). The effect is stronger for equal-weighted portfolios, with a monthly overnight (intraday) return spread of 2.08% (2.12%).

Second, an *asymmetric* "reversal" effect is observed, wherein CF Night (CF Day) is negatively associated with future intraday (overnight) returns of focal stocks. In particular, this reversal effect is more pronounced and robust when using peer stocks' overnight returns compared to peer stocks' intraday returns. The value-weighted CF Night strategy generates a monthly intraday return of -1.43% (t=-5.63), whereas the overnight return spread of the CF Day strategy is only -0.31% and marginally significant. Although the reversal effect of CF Day becomes more apparent (-0.87%) under equal weighting, it remains considerably weaker compared to CF Night (-1.99%). Notably, the intraday performance (1.40%) and overnight performance (-1.43%) of the CF Night strategy nearly offset each other, which explains the weak relationship between peer stocks' overnight returns and focal stocks' future close-to-close returns. While CF Day positively predicts focal stocks' future intraday returns, the reversal in future overnight returns is much weaker. This gives rise to the positive and strong predictive ability of peer stocks' intraday returns.

Figure 5 presents intraday and overnight strategy returns constructed from alternative economic linkage signals. The asymmetric cross-firm tug-of-war exists across these settings. Strategies based on peer firms' overnight returns earn positive returns overnight but negative returns intraday, with the magnitudes of the two legs broadly comparable. Intraday signals, in turn, are positively related to subsequent intraday returns, while their negative association with overnight returns is generally modest. Overall, these patterns are consistent with the findings under the shared analyst coverage setting.

[Insert Figure 5 about here]

B. Predicting intraday and overnight returns in regressions

Although the portfolio sorts approach is robust and does not impose a functional form on the relation I aim to study, it has difficulty controlling for other firm characteristics. In particular, focal stocks' own past intraday/overnight returns are important confounding factors that could affect the result. Therefore, I conduct Fama-MacBeth regressions that use intraday/overnight signals to forecast focal stocks' future intraday/overnight returns and control for other potential return predictors.

As a benchmark, I examine the predictive ability of CF RET, CF Day, and CF Night in regressions without controlling for the focal stocks' own past intraday or overnight returns. Table 5 reports the results. Also reported are the (scaled) difference between and the (scaled) sum of the coefficients from forecasting intraday returns and forecasting overnight returns (Lou et al., 2019).

The top row shows that CF RET positively predicts future overnight returns and intraday returns after controlling for other firm characteristics. The difference in the estimate between intraday and overnight is positive and significant, which is consistent with the portfolio result in Table 4.

For the intraday return signal, Table 5 shows that CF Day positively predicts focal stocks' future intraday returns. A one standard deviation increase in CF Day is associated with an increase in future intraday returns of 0.54%. Importantly, column (4) suggests that CF Day is not negatively related to future overnight returns after controlling for peer stocks' past overnight returns and focal stocks' other characteristics in regressions. The estimated coefficient on CF Day is 0.01 when forecasting overnight returns, representing only 2% in the magnitude of the estimate from forecasting intraday returns. The difference in the average slope of CF Day between intraday return regressions and overnight return regressions is also positive and significant.

For the overnight return signal, Table 5 suggests both a strong "continuation" in overnight returns and a stable "reversal" in intraday returns. Specifically, CF Night significantly predicts focal stocks' future intraday (overnight) returns in the opposite (same) direction. Columns (2) and (4) show that a one standard deviation increase in CF Night implies a 30 bps decrease (t=-4.88) in future intraday returns and a 44 bps (t=8.18) increase in future overnight returns.

Next, I control for the focal stock's own past monthly intraday return (Ret Day) and overnight return (Ret Night) as additional control variables.[11] This allows me to directly control for the own-firm tug-of-war effect of Lou et al. (2019). Table 6 reports the main results. For focal stocks' future intraday returns, I find that peer stocks' past returns still have strong predictive power. The estimated coefficient on CF Night (CF Day) is significantly negative (positive) at the 1%

[11]The focal stock's past one-month return (close-to-close) is excluded from regressions whenever Ret Day and Ret Night are controlled.

level. For focal stocks' future overnight returns, the estimated coefficient on CF Night is positive and robust. Similarly, I do not detect any overnight reversal effect using peer stocks' intraday returns. When predicting focal stocks' overnight returns, the estimated coefficient on CF Day is positive (0.096) and significantly smaller than the estimate from predicting intraday returns (0.444). Moreover, the (scaled) sum of coefficients on CF Night of predicting future intraday and overnight returns becomes insignificant (t=-1.49), consistent with the lack of predictive power of peer stocks' overnight returns for focal stocks' close-to-close returns.

[Insert Table 6 about here]

Overall, the regression results suggest an asymmetric tug-of-war (Lou et al., 2019) pattern in the context of cross-predictability: (1) an *inter-firm continuation* of overnight and intraday returns; (2) an *inter-firm daytime reversal* effect: high CF Night with low subsequent intraday returns; and (3) minor inter-firm overnight response: high CF Day followed by weak overnight price reactions.

C. Decomposing cross-firm return predictability

Based on previous findings, the lead-lag effect among connected stocks can be decomposed into four components, using the intraday and overnight signals of peer stocks as well as the intraday and overnight returns of the focal stock.[12] First, CF Night positively (negatively) forecasts focal stocks' future overnight (intraday) returns with a comparable magnitude. Second, CF Day positively predicts focal stocks' future intraday returns but does not exhibit clear negative predictive power for overnight returns. Consequently, CF Night is not significantly associated with future close-to-close returns as focal stocks' intraday and overnight price reactions offset each other. CF Day

[12]An illustration of the decomposition of cross-stock return predictability is presented in Figure 1.

generates a strong lead-lag returns relation since its positive predictive power for intraday returns dominates.

This asymmetric tug-of-war pattern is consistent with the two-clientele perspective of Lou et al. (2019) and Lou et al. (2024), and further suggests that trades among professional and retail investors contribute to the making of cross-predictability. Specifically, the focal stock's subsequent opening price continues to deviate from the fundamental value since individual traders are prone to being attracted by salient news, and engage in persistent speculative trading.[13] However, professional investors, who probably hold different perspectives on the focal stock and disagree with the opening price, dominate the market during the daytime period. As a result, focal stocks' intraday returns would exhibit an opposite movement due to the mismatch of effective demand.

For peer stocks' intraday returns, the delayed trading by intraday investors leads to the cross-stock continuation of intraday returns, which corrects focal stocks' prices, and anomaly returns result. As retail investors are attracted by overnight news more and overlook peer stocks' intraday returns, the focal stock's subsequent overnight return does not react significantly. Overall, the difference between intraday traders (more likely to be professional arbitrageurs) and overnight traders (more likely to be individuals) in their demands generates the observed cross-predictability pattern.

Figure 6 presents an example illustrating the mechanism discussed in this section. The decomposition results suggest several testable predictions regarding the story. First, CF Night should be positively associated with retail investors' trading, whereas institutions do not trade on overnight returns accordingly. Second, CF Day should be positively associated with professional

[13] For studies on the persistent and attention-driven trading by retail investors, see, for example, Barber and Odean (2008); Barber et al. (2008); Berkman et al. (2012); Engelberg et al. (2012); Aboody et al. (2018); McLean et al. (2025); Dong and Yang (2023), and Laarits and Sammon (2025).

trading, while retail investors do not react to intraday returns. Third, CF Night attracts retail investor attention more than CF Day does. Lastly, trading by daytime investors implies more accurate fundamentals for focal stocks, as it represents the correction of mispricing, whereas trades by overnight investors are driven by attention-grabbing signals. I test these predictions in the next section.

[Insert Figure 6 about here]

The proposed mechanism suggests that behavioral bias-induced mispricing (e.g., Barberis, Shleifer, and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyam (1998)) may not be the dominant driver of *overall* cross-firm momentum. The principal force, continuation of intraday returns across economically linked firms, is consistent with the slow movement of capital to trading opportunities (Mitchell et al., 2007; Duffie, 2010). Market frictions and capital constraints can prevent institutional investors from fully exploiting information they are able to process (Cohen, Gompers, and Vuolteenaho, 2002; Lewellen, 2011; Cao, Han, and Wang, 2017), generating spillovers across connected stocks.[14] The story in this paper highlights the role of institutional impediments, beyond behavioral inattention, in shaping price dynamics in an interconnected market.

V. Inspecting the mechanisms

In this section, I provide further evidence to examine the mechanisms underlying the overnight-intraday patterns of cross-stock return predictability. In particular, I will show the difference

[14] A related literature shows that investor clienteles also contribute to stocks' own momentum and reversal patterns. For instance, Chui, Subrahmanyam, and Titman (2022) and Du, Huang, Liu, Shi, Subrahmanyam, and Zhang (2025) document that noise trading by retail investors attenuates momentum and creates short-term reversals in China, whereas stocks with greater institutional participation exhibit momentum.

between peer stocks' intraday and overnight returns in predicting institutional investors' recognition and trading, retail investors' attention and purchase, and different types of order imbalance. I further distinguish the impact of professional trades and retail demands based on flows to mutual funds and hedge funds. I justify the trading behavior of professional and retail investors by examining focal stocks' realized fundamentals and intraday patterns of strategy returns. Finally, I conduct additional robustness tests. Unless otherwise noted, I control for focal stocks' own intraday and overnight returns in all regressions.

A. Evidence from institutional investors' recognition and trading

First, I validate the slow-moving arbitrage channel by examining the response of institutional investors. Prior research suggests that stock visibility and investor recognition are associated with an increase in the breadth of ownership (Merton, 1987; Chen et al., 2002; Grullon, Kanatas, and Weston, 2004). The testable prediction from my hypothesis is that the breadth of institutional ownership should react to peer stocks' intraday returns. Correspondingly, institutional investors would trade the focal stock based on CF Day as well.

To test this channel, I estimate the following regressions:

$$\begin{aligned}\Delta\text{BD}_{i,q+1} &= \alpha + \beta_{Day}\text{CF Day}_{i,q} + \beta_{Night}\text{CF Night}_{i,q} + Controls_{i,q} + \varepsilon_{i,q+1},\\ \Delta\text{INST}_{i,q+1} &= \alpha + \beta_{Day}\text{CF Day}_{i,q} + \beta_{Night}\text{CF Night}_{i,q} + Controls_{i,q} + \varepsilon_{i,q+1},\end{aligned} \tag{7}$$

where $\Delta\text{BD}_{i,q+1}$ is quarterly changes in the breadth of institutional investor ownership (Chen et al., 2002; Lehavy and Sloan, 2008); $\Delta\text{INST}_{i,q+1}$ is quarterly changes in institutional ownership, measuring institutional investors' trading (Edelen et al., 2016). Our hypothesis posits that $\beta_{Day} >$

0. Importantly, the association between institutional investors' subsequent trading and peer stocks' returns should be more pronounced for the intraday component than for the overnight component. Therefore, we also expect that $\beta_{Day} > \beta_{Night}$.

Table 7 reports the regression results. Columns (1) to (4) examine the subsequent change in the breadth of institutional investor ownership. First, I find that peer stocks' close-to-close returns (CF RET) are positively associated with future increases in institutional investor recognition. More importantly, it shows that CF Day positively forecasts subsequent ΔBD while CF Night is unrelated to future changes in the breadth of ownership. The difference in the estimated coefficients between CF Day and CF Night is significantly positive. A similar pattern is observed when predicting institutional investors' subsequent trading. For example, column (7) shows that a one-standard-deviation increase in lagged peer stocks' intraday returns is associated with a future increase in institutional ownership of 0.045%. In sharp contrast, the response of institutional trading to a one-standard-deviation increase in peer stocks' overnight returns is -0.009%.

[Insert Table 7 about here]

Overall, the difference in institutional investors' response to peer stocks' intraday and overnight returns supports the notion that institutions gradually execute arbitrage trading, and their trades do not rely on peer stocks' overnight returns. As a result, focal stocks' prices are corrected during the subsequent daytime period (i.e., a cross-stock continuation of intraday returns). Since the intraday effective demand does not match the opening price, a cross-stock daytime reversal occurs as prices converge to the fundamental value.[15]

[15]Note that institutions do not necessarily trade against peer stocks' overnight returns aggressively because of short-sell constraints. Akbas et al. (2021) find that when institutional investors overweight the noise trading contained in overnight returns and hence overcorrect prices, stocks tend to be underpriced and earn positive abnormal returns in the future. In later robustness tests, I examine this prediction in the cross-predictability context and find supportive evidence.

B. Evidence from retail investors' attention and purchase

The previous section supports the relevance between professional investors and intraday returns. In this section, I examine the relationship between retail investors and overnight returns. Specifically, previous studies demonstrate that overnight returns trigger retail investors' attention (Berkman et al., 2012; Engelberg et al., 2012; Aboody et al., 2018) and the trading preference of retail investors is persistent (Barber et al., 2008; Aboody et al., 2018; McLean et al., 2025; Dong and Yang, 2023; Laarits and Sammon, 2025). Therefore, we would expect the magnitude of CF Night to be positively related to future retail investor attention, and that CF Night positively predicts retail investor's purchase behavior. I estimate the following regressions:

$$\begin{aligned} \text{Attention}_{i,t+1} &= \alpha + \beta_{Day}|\text{CF Day}_{i,t}| + \beta_{Night}|\text{CF Night}_{i,t}| + Controls_{i,t} + \varepsilon_{i,t+1}, \\ \text{Net purchase}_{i,t+1} &= \alpha + \beta_{Day}\text{CF Day}_{i,t} + \beta_{Night}\text{CF Night}_{i,t} + Controls_{i,t} + \varepsilon_{i,t+1}, \end{aligned} \tag{8}$$

where $\text{Attention}_{i,t+1}$ is retail investor attention measured by abnormal Google search volume (Da et al., 2011); $\text{Net purchase}_{i,t+1}$ is calculated as the difference between retail buy volume and sell volume, divided by shares outstanding. We expect that $\beta_{Night} > 0$. Moreover, the relationship between retail investors and peer stocks' returns should be more pronounced for the overnight component than for the intraday component, that is, $\beta_{Night} > \beta_{Day}$.

Table 8 reports the regression results. The first two columns show that peer stocks' close-to-close returns are unrelated to retail investors' attention to the focal stock. When we separate the intraday and overnight components, however, columns (3) and (4) suggest a positive and significant relationship between the magnitude of peer stocks' overnight returns (|CF Night|) and retail investor attention. On the contrary, peer stocks' intraday returns do not facilitate attraction to the focal stock; if any, the estimated coefficient on |CF Day| is negative and insignificant. The last four columns examine retail investors' trading behavior. I find that retail investors tend to purchase the focal stock after experiencing a high peer stock return, a pattern predominantly driven by the overnight component. For example, column (7) shows that a one-standard-deviation increase in lagged CF Night implies an increase of 0.284 bps in net purchase of retail investors (t=5.20), while the effect from CF Day is only 0.020 (t=0.38). The difference in the estimated coefficients between CF Day and CF Night is -0.264 and statistically significant (t=-3.50).

[Insert Table 8 about here]

C. Evidence from order imbalance

This section further studies the difference in the demand between retail and professional investors. I examine two types of trading metrics: retail order imbalance and total order imbalance. As in the previous section, retail trades are identified by the Boehmer et al. (2021) algorithm. While it is challenging to directly identify professional investors' trades, the difference in the variation between retail order imbalance and total order imbalance would proxy for the trading behavior of more sophisticated investors. I examine the relationship between peer stocks' returns and the focal stock's subsequent order imbalance by estimating the following regression:

$$\text{Order imbalance}_{i,t+1} = \alpha + \beta_{Day}\text{CF Day}_{i,t} + \beta_{Night}\text{CF Night}_{i,t} + Controls_{i,t} + \varepsilon_{i,t+1}. \quad (9)$$

We expect that $\beta_{Night} > 0$ and $\beta_{Night} > \beta_{Day}$ for retail order imbalance, while $\beta_{Day} > 0$ and $\beta_{Day} > \beta_{Night}$ for total order imbalance.

Table 9 reports the regression results. The first six columns report the result based on retail order imbalance. Consistent with prior analysis, peer stocks' returns positively predict retail investors' purchases, and this process is primarily driven by the overnight component: the estimated coefficient on CF Night is positive and highly significant, while the coefficient on CF Day is minor. For total order imbalance, where professional traders hold greater sway, the pattern completely reverses. Specifically, columns (8), (10), and (12) show that CF Day positively and significantly predicts focal stocks' total order imbalance, whereas the coefficient on CF Night is negative, albeit insignificant. In all specifications, the difference in the estimated coefficients between CF Day and CF Night is significantly different from zero. This difference changes from negative to positive when shifting from retail order imbalance to total order imbalance.

[Insert Table 9 about here]

I also conduct two additional robustness tests. First, I examine order imbalance based on non-retail trades. Specifically, I define non-retail trades as total trades minus retail trades. Then, the non-retail order imbalance is calculated as non-retail buys minus non-retail sells, divided by the sum of non-retail buys and non-retail sells. Second, I examine institutional trading flows. Campbell, Ramadorai, and Schwartz (2009) estimate trading flows by mapping trades of different sizes into implied changes in institutional ownership. I obtain data on institutional trading flows from Tarun Ramadorai's website.[16] Consistent with the result using total order imbalance, Appendix Table A2 and Table A3 show that CF Day positively predicts subsequent non-retail order imbalance and institutional trading flows, whereas CF Night is negatively associated with these two additional trading metrics.

In sum, these findings support the mechanism discussed in Section C: (1) retail investors'

[16] I am grateful to the authors for making their data available. Address: `https://www.tarunramadorai.com/?section=1`

persistent trading on peer stocks' overnight returns leads to the cross-stock overnight return continuation; (2) professional investors' trades do not align with peer stocks' overnight returns, leaving effective intraday demand unable to sustain the deviated opening prices, which in turn generates cross-stock daytime reversals; (3) professional investors' subsequent trading corrects prices, while retail investors overlook peer stocks' intraday returns, resulting in the cross-stock intraday return continuation but marginal overnight price reactions.

D. Evidence from flows to mutual funds and hedge funds

An alternative way to differentiate the impact of retail versus more sophisticated investors' demand is by analyzing fund flows (Frazzini and Lamont, 2008; Jagannathan, Malakhov, and Novikov, 2010; Lou, 2012; Akbas et al., 2015; Barber, Huang, and Odean, 2016). For instance, Akbas et al. (2015) use mutual fund flows to proxy for "dumb" money and hedge fund flows as a proxy for "smart" money. This approach enables me to examine potential *time-variation* in the predictability of intraday and overnight returns across firms.

Specifically, increases in mutual fund flows imply intensified retail investor participation, and fund managers also tend to purchase stocks that align with retail investors' attention (Lou, 2012; Agarwal, Jiang, and Wen, 2022). This implies that increased mutual fund flows should predict a stronger cross-firm continuation of overnight returns.[17] Accordingly, the cross-firm daytime reversal effect should also be more pronounced, as the opening price deviates further from the fundamental value. In contrast, increased hedge fund flows should be associated with a

[17] Early studies, such as Edelen and Warner (2001) and Ben-Rephael, Kandel, and Wohl (2011), also find that flow-induced trading could exert substantial pressure on opening prices.

stronger cross-firm continuation of intraday returns, driven by greater entry of arbitrage capital and, consequently, more effective price correction.

In Table 10, I conduct several time-series regressions to investigate the time variation in different components of return predictability, specifically the cross-firm tug-of-war (ToW), based on flows to mutual funds (MFFLOW) and flows to hedge funds (HFFLOW):

$$ToW_{t+1} = \alpha + \beta_{MF}^{ToW} MFFLOW_t + \beta_{HF}^{ToW} HFFLOW_t + Controls + \varepsilon_{t+1}, \tag{10}$$

where ToW_{t+1} represents the intraday/overnight return of the high-minus-low portfolio formed by CF Night/CF Day, as previously examined in Table 4: (1) Night-to-Night, the overnight return of the high-minus-low portfolio formed by CF Night; (2) Night-to-Day, the intraday return of the high-minus-low portfolio formed by CF Night; (3) Day-to-Night, the overnight return of the high-minus-low portfolio formed by CF Day; and (4) Day-to-Day, the intraday return of the high-minus-low portfolio formed by CF Day.

Column (1) shows that MFFLOW is positively associated with the continuation of overnight returns, with the estimated coefficient ($\beta_{MF}^{\text{Night-to-Night}}$) being highly significant (t=3.24). This suggests that trades driven by unsophisticated investors' demand (i.e., "dumb money") contribute to price distortions at market openings. Aligning with this result, column (2) shows that increased MFFLOW also leads to stronger daytime reversals ($\beta_{MF}^{\text{Night-to-Day}}$=-0.672). In column (4), I examine the relationship between fund flows and intraday return continuation. The estimated coefficient on HFFLOW is positive and significant ($\beta_{HF}^{\text{Day-to-Day}}$=0.599), indicating that new flows of "smart money" facilitate price correction. Overall, the time variation in the cross-firm tug-of-war complements my previous findings that differences in demand between individual and professional traders are key drivers of the observed predictability patterns.

[Insert Table 10 about here]

E. The information content of peer stocks' returns

As illustrated in Figure 6, the promise underlying the cross-firm tug-of-war is that professional investors' delayed trading corrects prices while retail investors' persistent trading introduces price distortion. To justify this story, peer stocks' high intraday returns should predict favorable fundamentals for focal stocks. For peer stocks' overnight returns, there are two potential scenarios: (1) peer stocks' overnight returns are pure noise and the cross-stock continuation of overnight returns merely reflects the persistency of sentiment; (2) peer stocks' overnight returns are informative about focal stocks' fundamentals in different dimensions and retail investors overreact to these salient news.

In this section, I examine the difference between CF Day and CF Night in predicting focal stocks' subsequent fundamentals by estimating the following regression:

$$\text{Fundamental}_{i,q+1} = \alpha + \beta_{Day}\text{CF Day}_{i,q} + \beta_{Night}\text{CF Night}_{i,q} + Controls_{i,q} + \varepsilon_{i,q+1}. \tag{11}$$

I consider two types of fundamental variables. The first type focuses on focal firms' earnings news and profitability, including standardized unexpected earnings (SUE), return-on-assets (ROA), and gross profitability (GP); the second type focuses on focal firms' investment and growth potential, including asset growth (AG), sales growth (SG), and revenue growth (RG).

Table 11 reports the regression results. I find that peer stocks' intraday returns positively and significantly predict focal stocks' earnings and profitability in the next quarter, consistent with the arbitrage trading story. Interestingly, peer stocks' overnight returns are also informative about focal stocks' future profitability but in the *opposite* direction. Specifically, CF Night negatively predicts SUE, ROA, and GP in the subsequent quarter, suggesting a potential overreaction by retail traders.

While CF Day is positively associated with focal stocks' future profitability, Table 11 shows that peer stocks' intraday return is not a strong predictor for growth in fundamentals. In contrast, CF Night positively and significantly forecasts focal stocks' growth in total assets (AG), sales (SG), and revenues (RG). These results suggest that both peer stocks' intraday and overnight returns are informative about focal stocks' future fundamentals, but they differ substantially. The fact that CF Night positively predicts fundamental growth but negatively predicts profitability suggests that retail investors' persistent trading tends to be driven by the salience of news and the pursuit of glamour stocks (e.g., Lakonishok et al. (1994), La Porta (1996), La Porta, Lakonishok, Shleifer, and Vishny (1997), and Barber and Odean (2008)). As a result, following high (low) CF Night, the focal stock's opening price deviates upwards (downwards) from the rational benchmark because of retail investors' continued trading. The focal stock's price converges to the fundamental value when professional investors dominate the market (i.e., during the daytime) and value-relevant information is incorporated.

[Insert Table 11 about here]

F. Evidence from intraday patterns

Previous tests focus on heterogeneous investor behavior. During the intraday period, professional arbitrageurs incorporate the information contained in CF Day and correct the mispricing triggered by CF Night. In this section, I delve into the intraday return patterns to further validate the story of this paper.[18] Bogousslavsky (2021) suggests that holding positions overnight is both costly and risky. Therefore, arbitrageurs who exploit mispricing typically initiate trades early in the day and then slow down activity or even reverse positions by the market close. As a result, mispricing is mainly corrected early in the day, while it tends to worsen toward the end of the day because of the price pressure from closing positions. My hypothesis, combined with the theory of Bogousslavsky (2021), predicts two intraday patterns of cross-firm return predictability. The first is a direct implication of Bogousslavsky (2021). We expect that the positive intraday returns of the CF Day strategy materialize mainly early in the day. Second and more importantly, the cross-firm tug-of-war should exhibit a similar pattern. We expect that the negative intraday returns of the CF Night strategy also appear early in the day and then become attenuated or even reverse by the market close.

I decompose intraday returns into 15-minute intervals between 9:45 am and 4:00 pm, and then calculate interval returns based on quote midpoints.[19] For each stock-month, I calculate the cumulative return for each of these intraday intervals. Figure 7 presents intraday interval returns of strategies formed by CF Day and CF Night. Consistent with the channel of Bogousslavsky (2021), the intraday return of the CF Day strategy is positive and significant for most intervals over the first half of the day. However, the return becomes negative during the last 15-minute interval. Moreover, the cross-firm tug-of-war displays a consistent pattern. The intraday return of the CF

[18] I am grateful to the anonymous referee for suggesting this test and providing valuable insights.

[19] Following Bogousslavsky (2021) and Jiang, Li, and Wang (2021), I use the intraday window starting at 9:45 am to mitigate the impact of potentially inaccurate opening quotes and ensures that most stocks have recorded at least one trade after the market opens. Quote midpoint is defined as the midpoint of best bid and best offer taken from the National Best Bid and Offer (NBBO) files. Intraday quote price data used in this section is obtained from TAQ. As a robustness check, Appendix C3 also examines cross-firm tug-of-war using the volume-weighted average price in the first 15-minute interval of trading (9:30 am to 9:45 am) to measure the opening price. The paper's main findings remain valid under this alternative opening price definition.

Night strategy is -0.368% (t=-4.72) and -0.344% (t=-6.84) per month in the first two 15-minute intervals, and tends to decline in magnitude throughout the day. In the last 15-minute interval, the CF Night strategy earns a significantly positive return of 0.144% (t=5.99). These intraday patterns of cross-predictability align well with the argument of Bogousslavsky (2021) and further support the story proposed in this paper.

[Insert Figure 7 about here]

G. Additional robustness tests

I conduct a series of robustness tests in Appendix C to complement my main analysis. The first set of tests focuses on the cross-predictability patterns. Appendix C1 shows that the inter-firm continuation of overnight returns and the inter-firm daytime reversal effect exhibit high persistence. This pattern aligns with retail investors' trading being persistent. Appendix C2 shows that the predictability result of the paper is invariant to the choice of signal formation period or holding horizons. Appendix C3 reports results using the volume-weighted average price in the first 15-minute interval of trading (9:30 am to 9:45 am) as the opening price. The asymmetric cross-firm tug-of-war pattern remains robust under this specification. Appendix C4 further explores cross-predictability at the daily frequency. Appendix C5 shows that my findings cannot be solely explained by the information discreteness channel (Da et al., 2014; Huang et al., 2022).

Second, I expand my analysis by implementing the empirical designs in two related studies. Burt and Hrdlicka (2021) propose a method of dissecting cross-stock predictability by decomposing signals into two components: (1) a predictable component related to commonality in characteristics-based factors; and (2) an idiosyncratic component reflecting news. They show that both components contribute almost equally to monthly returns of cross-predictability strategy. Therefore, underreaction to news is not the only source of this anomaly. Following their approach, I further decompose CF Day and CF Night into the *Common* component and the *News* component, and re-examine their predictive ability for subsequent returns. Aligning with the argument of Burt and Hrdlicka (2021), results in Appendix C6 show that both components contribute significantly to the predictability pattern documented in this paper.

Akbas et al. (2021) suggest that a prolonged tug-of-war reflects daytime arbitrageurs' overcorrection behavior as they overweight the influence of noise trading on overnight returns. This story predicts that the focal stock tends to be underpriced if the cross-firm tug-of-war is intense. Consistent with this prediction, results in Appendix C7 show that the abnormal frequency of cross-firm negative daytime reversals (i.e., a positive peer overnight return followed by the focal stock's negative intraday return) positively predicts focal stocks' future close-to-close returns.

VI. Conclusion

The lead-lag returns relation among economically linked firms has received great attention in empirical asset pricing studies. As the literature is experiencing a surge in uncovering economic connections from multiple contexts, it is crucial to understand the generating process of cross-firm return predictability. This paper shows an inter-firm, *asymmetric* tug-of-war (Lou et al., 2019), characterized by a strong continuation of overnight and intraday returns, a daytime reversal effect, but minor overnight price reactions. It follows that cross-predictability primarily relies on peer stocks' intraday returns and disappears for peer stocks' overnight returns.

These results highlight the importance of investor composition and demand shocks in generating the predictable return patterns among connected firms. The decomposition procedure could also serve as a tool for testing and categorizing new economic connections. It would be highly beneficial for future work to develop theoretical models to formalize the overnight-intraday price dynamics among linked stocks and unveil deeper mechanisms of interdependence in financial markets.

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FIGURE 1

Decomposition of lead-lag returns relation

This figure depicts the decomposition of cross-firm return predictability. We partition both peer- and focal-firms' monthly returns into the overnight and the intraday components. Peer firms' average overnight return in month t positively (negatively) predicts focal firms' overnight (intraday) return in month $t+1$; peer firms' average intraday return positively predicts focal firms' intraday return in month $t+1$, while displaying only a weak association with focal firms' subsequent overnight return.

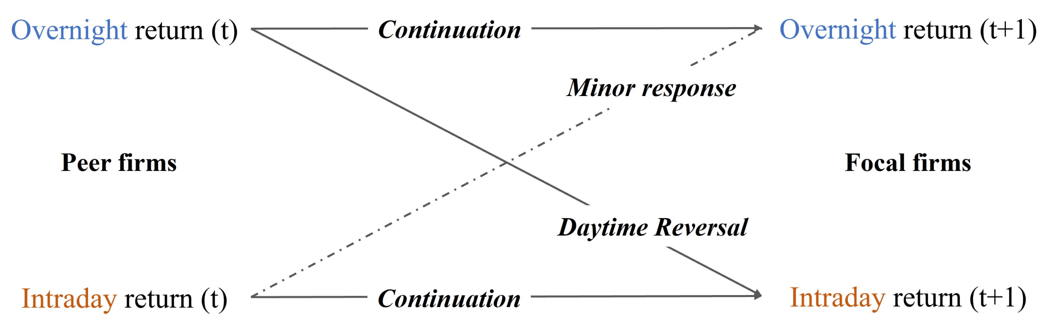

FIGURE 2

Strategy returns based on shared analyst coverage signals

This figure plots the average returns and Carhart (1997) alphas of the shared analyst coverage strategies based on the 24-hour signal (CF RET), the intraday return signal (CF Day), and the overnight return signal (CF Night), respectively. Each month, two stocks are defined as connected if at least one analyst covered both stocks in the previous 12 months. CF RET is the connected-firm portfolio return constructed following Ali and Hirshleifer (2020). CF Day and CF Night are respectively intraday and overnight return signals, calculated using the same procedure as CF RET by replacing peer stocks' monthly close-to-close returns with monthly intraday and overnight returns. Each month, stocks are sorted into quintile portfolios based on peer firm returns. Portfolios are held for one month. Blue bars represent equal-weighted returns, whereas gray bars represent value-weighted returns. The strategy is the hedge portfolio that longs stocks in the top quintile and shorts stocks in the bottom quintile. The sample period is from July 1992 to December 2021.

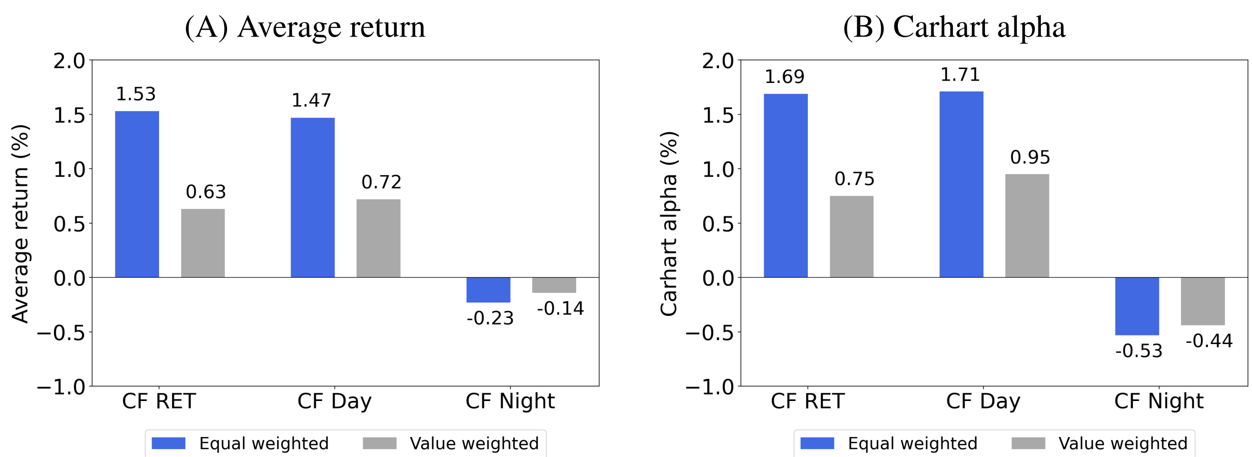

FIGURE 3

Strategy returns based on alternative lead-lag settings

This figure presents the lead-lag returns relation of settings based on the Fama-French 49 industry classification (INDFF), the three-digit SIC codes industry classification (INDSIC), the text-based industry classification (INDTIC), geographic links (GEO), technological links (TECH), and conglomerate firms (CONGLM). For each setting, stocks each month are divided into five groups based on the 24-hour signal, the day signal, and the night signal, respectively. Then, equal-weighted portfolios are formed and held for one month. The figure reports profits of the long-short strategy measured by close-to-close returns. The sample period is from July 1992 to December 2021.

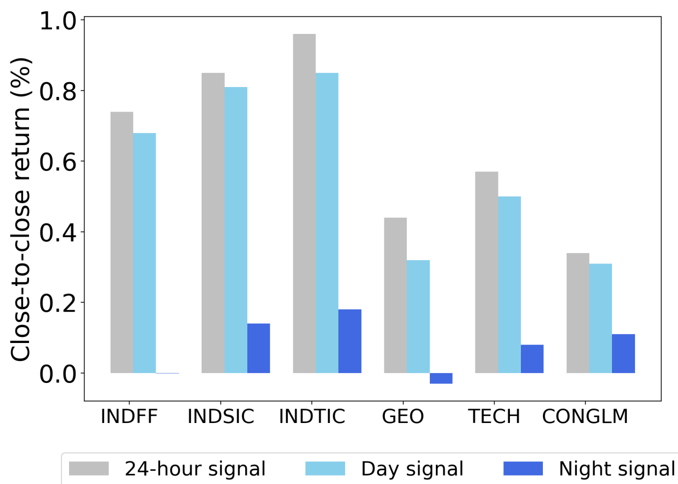

FIGURE 4

Intraday and overnight returns based on CF Day and CF Night

This figure plots the average intraday and overnight returns of the shared analyst coverage strategies based on CF Day (left panel) and CF Night (right panel), respectively. Each month, two stocks are defined as connected if at least one analyst covered both stocks in the previous 12 months (Ali and Hirshleifer, 2020). CF Day and CF Night represent the intraday and overnight returns, respectively, of the connected-firm portfolio. Each month, stocks are sorted into quintiles based on CF Day (left panel) and CF Night (right panel). The return of the long-short strategy of buying stocks within the top quintile and selling those within the bottom quintile is calculated. Blue bars represent equal-weighted returns, whereas gray bars represent value-weighted returns. The sample period is from July 1992 to December 2021.

(A) CF Day strategy (B) CF Night strategy

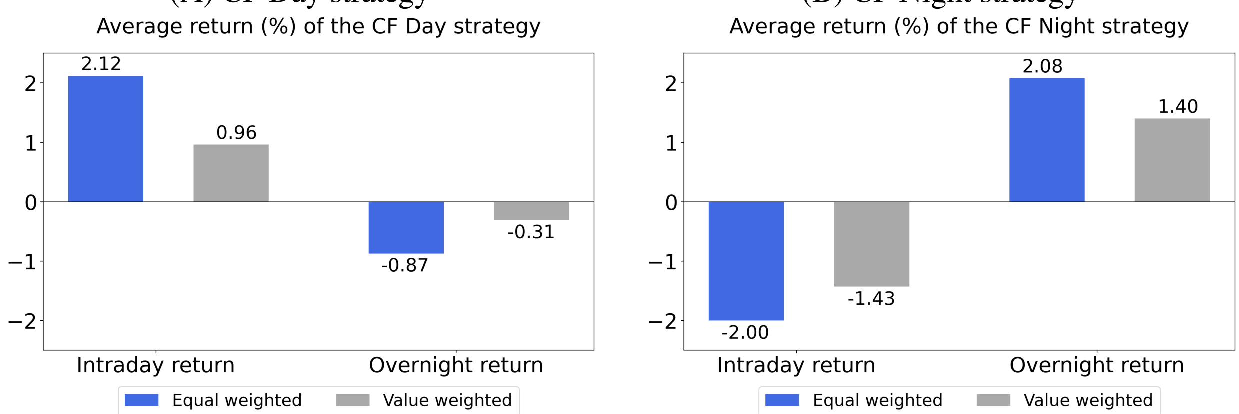

FIGURE 5

Intraday and overnight returns based on alternative lead-lag settings

This figure presents the lead-lag returns relation of settings based on the Fama-French 49 industry classification (INDFF), the three-digit SIC codes industry classification (INDSIC), the text-based industry classification (INDTIC), geographic links (GEO), technological links (TECH), and conglomerate firms (CONGLM). For each setting, stocks each month are divided into five groups based on the 24-hour signal, the day signal, and the night signal, respectively. Then, equal-weighted portfolios are formed and held for one month. The figure reports profits of the long-short strategy measured by intraday returns and overnight returns. The sample period is from July 1992 to December 2021.

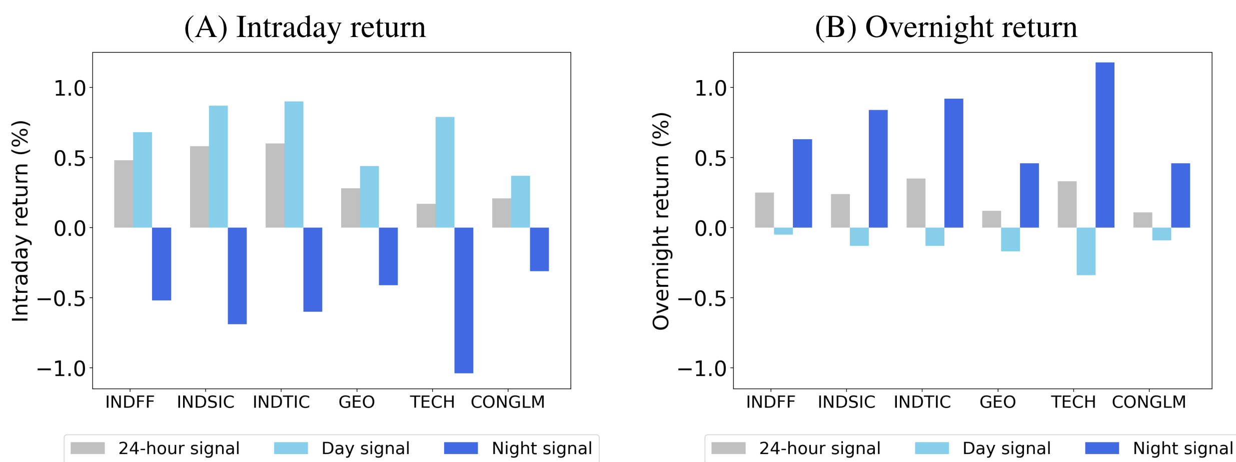

FIGURE 6

Illustration of mechanism

This figure depicts the mechanism underlying cross-predictability among economically linked stocks. For illustration, it considers scenarios of positive shocks to peer stocks' overnight returns or intraday returns.

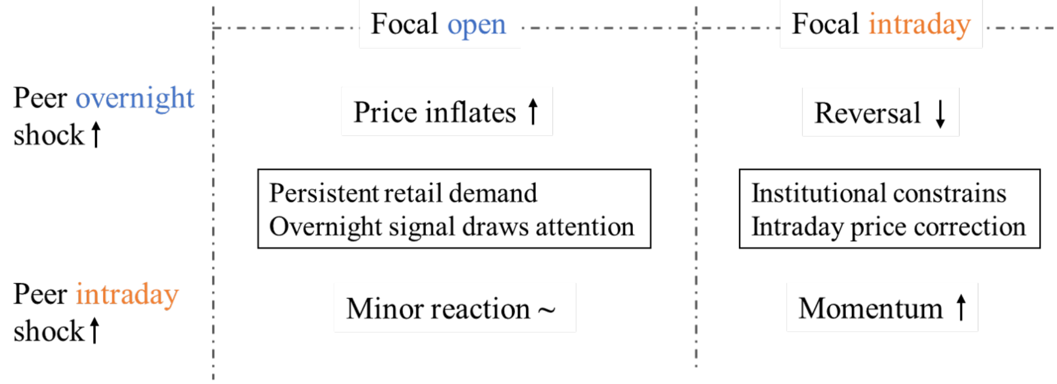

FIGURE 7

Intraday return patterns of CF Day and CF Night strategies

This figure shows average interval returns and t-statistics of CF Day and CF Night strategies throught the intraday period. For each trading day from 09:45 to 16:00, I calculate 15-minute interval returns using midpoint prices. Then, I calculate cumulative interval returns within the month. At the end of each month, stocks are ranked into quintiles based on CF Day and CF Night, respectively. The CF Day (CF Night) strategy longs stocks within the top quintile and shorts those within the bottom quintile. The figure shows the performance of these strategies during different time intervals throught the intraday period. Dashed lines in the bottom figure indicate significance at the level of 10%. The t-statistics are calculated based on Newey and West (1987) standard errors. Portfolios are monthly rebalanced and stocks are equally weighted. The sample period is from January 1993 to December 2021.

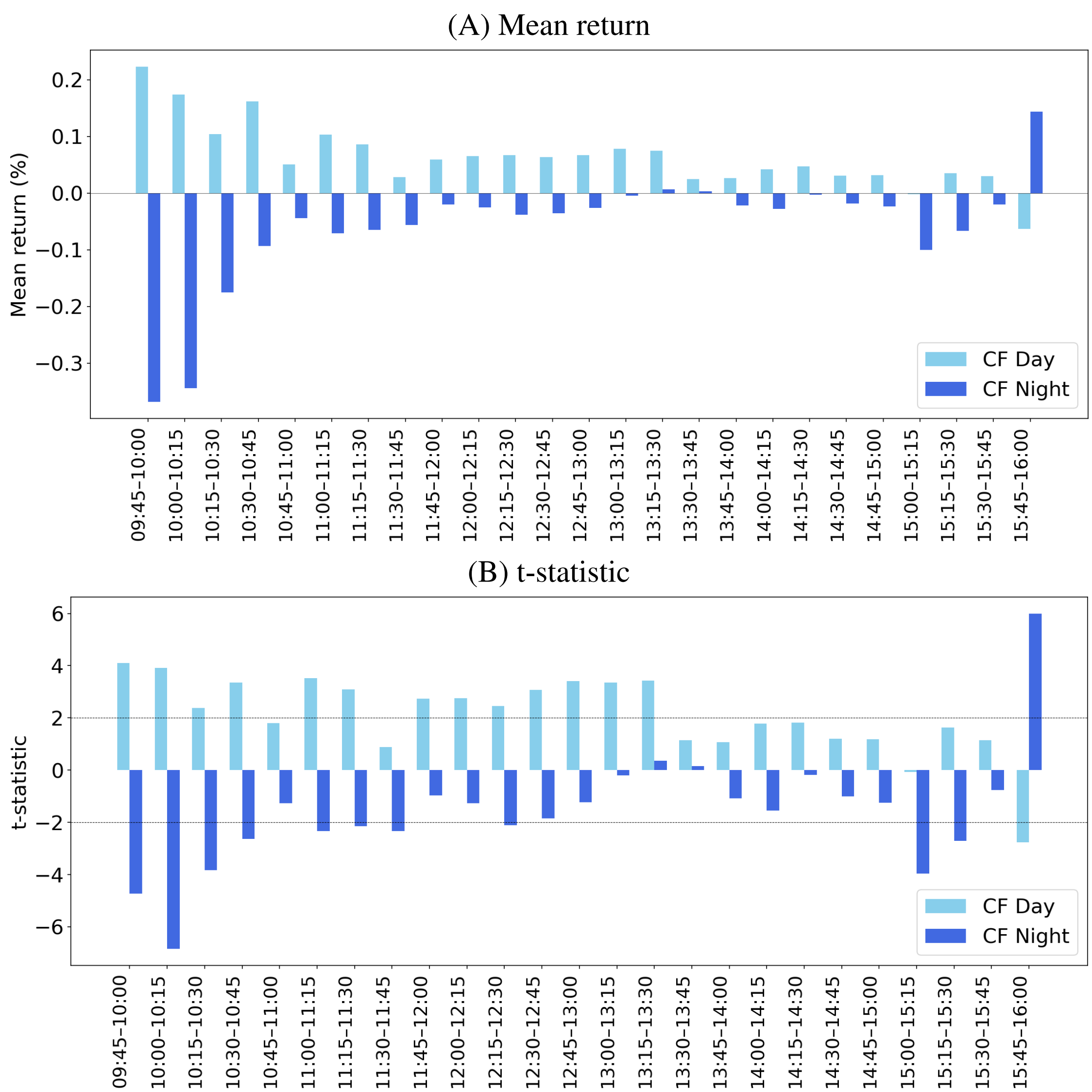

TABLE 1

Summary statistics

This table presents summary statistics for variables used in the analysis. Panel A reports variables related to the shared analyst coverage sample, including the number of peer firms connected to each stock (# connected firms); the proportion of stocks covered by the sample, by count and by market capitalization; connected-firm portfolio return (CF RET, in %); connected-firm intraday return (CF Day, in %); and connected-firm overnight return (CF Night, in %). Panel B reports focal stocks' own monthly returns (in %), including the close-to-close return (Ret CC), intraday return (Ret Day), and overnight return (Ret Night). Panel C presents variables related to institutional and retail investors, including quarterly changes in the breadth of institutional ownership (ΔBD, in %) following Chen et al. (2002) and Lehavy and Sloan (2008); quarterly changes in institutional ownership (ΔINST, in %) following (Edelen et al., 2016); retail investor attention measured by abnormal Google search volum, following (Da et al., 2011); and net purchase of retail investors (in %) based on the Boehmer et al. (2021) algorithm. Panel D reports the average daily order imbalance over a month, computed by trade count, trading volume, and dollar value; retail order imbalance is again calculated using the Boehmer et al. (2021) algorithm. Panel E reports flows to mutual funds (MFFLOW) and hedge funds (HFFLOW), measured as in Akbas et al. (2015) and reported in percent. Due to variations in data availability, the sample spans 2004 to 2020 for retail investor attention, 2007 to 2021 for retail net purchase and order imbalance, and 1994 to 2021 for MFFLOW and HFFLOW. For other variables, the sample period is from July 1992 to December 2021.

Item	Mean	Std.dev.	Min	P1	P10	Median	P90	P99	Max
Panel A. Shared analyst coverage									
# connected firms	77	48.7	1	6	23	68	144	224	312
Number of stocks covered	0.820	0.054	0.703	0.712	0.739	0.811	0.889	0.902	0.905
Market capitalization covered	0.980	0.010	0.951	0.955	0.962	0.980	0.990	0.993	0.993
CF RET	1.214	4.607	-21.865	-9.432	-4.083	1.119	6.539	13.191	32.408
CF Day	0.237	4.403	-26.022	-10.75	-4.941	0.384	5.086	10.651	32.266
CF Night	1.550	2.842	-14.883	-3.645	-1.034	1.138	4.613	10.37	35.911
Panel B. Focal firms' own returns									
Ret CC	2.102	15.207	-57.24	-28.002	-11.935	0.882	16.496	46.925	259.859
Ret Day	1.476	14.618	-55.962	-30.295	-13.347	0.667	16.276	44.895	209.255
Ret Night	1.047	10.523	-55.171	-23.161	-8.104	0.379	10.393	33.025	161.612
Panel C. Institutional and retail investors									
Institutional recognition (ΔBD)	0.075	0.631	-6.494	-1.417	-0.447	0.038	0.658	1.652	8.842
Institutional trading (ΔINST)	0.560	6.291	-58.889	-15.387	-4.236	0.300	5.526	18.714	69.945
Retail investor attention	-0.104	0.601	-3.488	-2.256	-0.644	-0.022	0.350	1.104	2.666
Retail investor net purchase	0.004	0.649	-2.551	-0.505	-0.127	-0.009	0.104	0.573	23.329
Panel D. Order imbalance									
Total trade imbalance	-0.006	0.055	-0.466	-0.170	-0.060	-0.004	0.046	0.137	0.408
Total volume imbalance	-0.010	0.059	-0.523	-0.196	-0.070	-0.007	0.047	0.135	0.407
Total value imbalance	-0.009	0.059	-0.521	-0.194	-0.069	-0.006	0.048	0.136	0.410
Retail trade imbalance	-0.020	0.114	-0.754	-0.347	-0.151	-0.015	0.105	0.257	0.640
Retail volume imbalance	-0.027	0.117	-0.796	-0.365	-0.161	-0.020	0.098	0.256	0.656
Retail value imbalance	-0.027	0.117	-0.796	-0.365	-0.16	-0.019	0.098	0.257	0.657
Panel E. Fund flows									
MFFLOW	0.067	0.602	-1.767	-1.251	-0.575	0.013	0.888	1.613	2.174
HFFLOW	0.317	1.575	-10.037	-5.292	-1.167	0.421	1.969	3.618	4.781

TABLE 2

Performance of shared analyst coverage strategies

This table reports one-sort portfolio results by sorting stocks based on CF RET, CF Day, and CF Night, respectively. Each month, two stocks are defined as connected if at least one analyst covered both stocks in the previous 12 months. CF RET is the connected-firm portfolio return constructed following Ali and Hirshleifer (2020). CF Day and CF Night are respectively intraday and overnight return signals, calculated using the same procedure as CF RET by replacing peer stocks' close-to-close returns with intraday and overnight returns. The table presents returns, four-factor alphas (Carhart, 1997), and seven-factor (the Fama-French five factors, momentum factor, and short-term reversal factor) alphas. Portfolios are value weighted in Panel A and equal weighted in Panel B. The sample period is from July 1992 to December 2021. The t-statistics with Newey and West (1987) adjusted standard errors are shown in parentheses.

Panel A. Value weighted

Quintile	Excess return			Carhart alpha			FF7 alpha		
	CF RET	CF Day	CF Night	CF RET	CF Day	CF Night	CF RET	CF Day	CF Night
Low	0.377	0.363	0.888	-0.503	-0.567	0.258	-0.537	-0.476	0.053
	(1.22)	(1.20)	(3.76)	(-2.86)	(-3.41)	(2.33)	(-4.45)	(-3.83)	(0.47)
2	0.855	0.816	0.763	0.017	0.027	0.046	0.002	-0.034	-0.084
	(3.50)	(3.17)	(3.37)	(0.13)	(0.25)	(0.51)	(0.02)	(-0.34)	(-0.89)
3	0.796	0.735	0.857	0.056	-0.045	0.127	-0.067	-0.183	-0.020
	(3.21)	(2.98)	(3.69)	(0.73)	(-0.63)	(1.74)	(-0.74)	(-2.23)	(-0.29)
4	0.947	0.996	0.665	0.261	0.278	-0.107	0.232	0.173	-0.088
	(3.82)	(3.97)	(2.58)	(2.85)	(2.97)	(-1.08)	(2.71)	(2.07)	(-0.85)
High	1.011	1.078	0.746	0.261	0.382	-0.186	0.393	0.537	0.194
	(3.40)	(3.87)	(1.96)	(1.78)	(2.77)	(-1.10)	(2.52)	(3.29)	(1.19)
High-Low	0.634	0.715	-0.142	0.764	0.948	-0.444	0.929	1.013	0.141
	(2.11)	(2.71)	(-0.45)	(2.62)	(3.53)	(-1.85)	(3.89)	(4.11)	(0.60)

Panel B. Equal weighted

Quintile	Excess return			Carhart alpha			FF7 alpha		
	CF RET	CF Day	CF Night	CF RET	CF Day	CF Night	CF RET	CF Day	CF Night
Low	-0.029	-0.013	0.854	-1.059	-1.069	0.070	-1.077	-0.955	-0.079
	(-0.08)	(-0.03)	(2.84)	(-6.48)	(-7.34)	(0.65)	(-7.60)	(-7.56)	(-0.79)
2	0.606	0.695	0.841	-0.296	-0.233	0.020	-0.335	-0.291	-0.155
	(1.98)	(2.27)	(2.91)	(-3.03)	(-2.98)	(0.21)	(-3.55)	(-3.38)	(-1.94)
3	0.937	0.832	0.975	0.102	-0.019	0.114	0.029	-0.097	0.017
	(3.19)	(2.83)	(3.31)	(1.34)	(-0.26)	(1.53)	(0.39)	(-1.40)	(0.27)
4	1.170	1.207	0.885	0.336	0.394	-0.035	0.332	0.337	0.060
	(3.78)	(4.09)	(2.74)	(3.52)	(4.40)	(-0.45)	(3.96)	(4.48)	(0.75)
High	1.497	1.459	0.624	0.630	0.641	-0.455	0.785	0.740	-0.109
	(3.96)	(4.28)	(1.42)	(3.76)	(4.73)	(-3.18)	(4.54)	(4.98)	(-0.97)
High-Low	1.526	1.473	-0.229	1.689	1.710	-0.526	1.862	1.695	-0.030
	(4.50)	(5.31)	(-0.75)	(5.55)	(6.80)	(-2.46)	(6.45)	(6.83)	(-0.18)

TABLE 3

Fama-MacBeth regressions

This table reports the time-series averages of coefficients from monthly cross-sectional regressions. The dependent variable is the focal stock's close-to-close return in the subsequent month (in percentage). Each month, two stocks are defined as connected if at least one analyst covered both stocks in the previous 12 months. CF RET is the connected-firm portfolio return constructed following Ali and Hirshleifer (2020). CF Day and CF Night are respectively intraday and overnight return signals, calculated using the same procedure as CF RET by replacing peer stocks' close-to-close returns with intraday and overnight returns. I control for the focal stock's own past monthly close-to-close return (Ret CC) or the past intraday return (Ret Day) and overnight return (Ret Night). Other control variables include the past 12-month return with a 1-month gap, log of market capitalization, log of book-to-market ratio, the idiosyncratic volatility of Ang et al. (2006), and the illiquidity measure of Amihud (2002). Independent variables are winsorized at 1% and 99% each month and standardized to have zero mean and unit variance. The last row (CF Day−CF Night) reports the difference between the estimated coefficients on CF Day and CF Night. The sample period is from July 1992 to December 2021. The t-statistics with Newey and West (1987) adjusted standard errors are shown in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
CF RET	0.556		0.514		0.518	
	(4.40)		(5.03)		(5.06)	
CF Day		0.615		0.563		0.573
		(5.63)		(6.30)		(6.36)
CF Night		0.073		0.090		0.084
		(0.68)		(1.06)		(1.01)
Ret CC			√	√		
Ret Day					√	√
Ret Night					√	√
Controls			√	√	√	√
Intercept	1.023	1.023	1.044	1.036	1.048	1.039
	(3.38)	(3.38)	(3.45)	(3.41)	(3.46)	(3.42)
Avg. R^2(%)	1.773	2.413	5.489	5.838	5.576	5.909
Avg. # Obs	2458	2458	2268	2268	2268	2268
CF Day−CF Night		0.542		0.473		0.490
		(5.21)		(5.79)		(6.06)

TABLE 4

Intraday/overnight performance of shared analyst coverage strategies

This table reports one-sort portfolio results by sorting stocks based on CF RET, CF Day, and CF Night, respectively. For each signal, I separately track future one-month intraday/overnight returns of portfolios. CF RET is the connected-firm portfolio return constructed following Ali and Hirshleifer (2020). CF Day and CF Night are respectively intraday and overnight return signals, calculated using the same procedure as CF RET. The return of the long-short strategy of buying the top signal quintile stocks and selling the bottom signal quintile stocks is presented in the "Excess return" column, and the corresponding alpha relative to the seven-factor model is reported in the "FF7 alpha" column. Portfolios are value weighted in Panel A and equal weighted in Panel B. The sample period is from July 1992 to December 2021. The t-statistics with Newey and West (1987) adjusted standard errors are shown in parentheses.

Panel A. Value weighted

Return type	Signal	Low	2	3	4	High	Excess return	FF7 alpha
Intraday	CF RET	-0.466	0.251	0.213	0.200	0.027	0.493	0.682
		(-1.83)	(1.42)	(1.12)	(1.04)	(0.14)	(2.10)	(3.21)
	CF Day	-0.618	0.008	0.150	0.371	0.346	0.964	1.146
		(-2.37)	(0.04)	(0.82)	(2.08)	(1.81)	(3.97)	(4.36)
	CF Night	0.648	0.394	0.222	-0.227	-0.784	-1.431	-1.271
		(3.62)	(2.49)	(1.25)	(-1.07)	(-2.52)	(-5.63)	(-5.06)
Overnight	CF RET	0.844	0.525	0.510	0.667	0.934	0.090	0.201
		(4.75)	(3.31)	(2.87)	(3.70)	(3.77)	(0.42)	(1.13)
	CF Day	0.990	0.751	0.502	0.534	0.679	-0.311	-0.195
		(4.66)	(4.57)	(3.05)	(2.85)	(3.09)	(-1.65)	(-1.11)
	CF Night	0.177	0.274	0.540	0.838	1.573	1.397	1.528
		(1.15)	(1.67)	(3.15)	(4.17)	(5.03)	(4.46)	(5.01)

Panel B. Equal weighted

Return type	Signal	Low	2	3	4	High	Excess return	FF7 alpha
Intraday	CF RET	-0.692	0.261	0.595	0.657	0.582	1.274	1.425
		(-2.05)	(1.01)	(2.39)	(2.68)	(2.16)	(5.08)	(6.25)
	CF Day	-1.081	0.153	0.489	0.799	1.043	2.123	2.205
		(-2.96)	(0.60)	(1.93)	(3.36)	(4.05)	(7.53)	(8.18)
	CF Night	1.035	0.687	0.555	0.087	-0.962	-1.997	-1.843
		(4.20)	(2.92)	(2.35)	(0.32)	(-2.55)	(-7.48)	(-7.47)
Overnight	CF RET	1.031	0.558	0.520	0.683	1.157	0.125	0.309
		(4.95)	(3.03)	(2.72)	(3.11)	(4.00)	(0.58)	(1.70)
	CF Day	1.509	0.739	0.506	0.552	0.640	-0.868	-0.742
		(5.99)	(3.90)	(2.66)	(2.63)	(2.65)	(-4.74)	(-4.31)
	CF Night	0.020	0.256	0.549	1.024	2.099	2.080	2.141
		(0.11)	(1.51)	(2.94)	(4.47)	(5.78)	(6.56)	(6.66)

TABLE 5

Fama-MacBeth regressions: intraday and overnight returns

This table reports the time-series averages of coefficients from monthly cross-sectional regressions. The dependent variable in the first two columns is the focal stock's subsequent intraday return (in percentage); the dependent variable in the third and fourth columns is the focal stock's overnight return in the following month (in percentage). Columns (5) and (6) report the scaled difference between and the scaled sum of the intraday coefficient$\times 24/6.5$ and the overnight coefficient$\times 24/17.5$. Each month, two stocks are defined as connected if at least one analyst covered both stocks in the prior 12 months. CF RET is the connected-firm portfolio return constructed following Ali and Hirshleifer (2020). CF Day and CF Night are respectively intraday and overnight return signals, calculated using the same procedure as CF RET. Control variables include the past 1-month return (close-to-close), past 12-month return with a 1-month gap, log of market capitalization, log of book-to-market ratio, the idiosyncratic volatility of Ang et al. (2006), and illiquidity measure of Amihud (2002). Independent variables are winsorized at 1% and 99% each month and standardized to have zero mean and unit variance. The sample period is from July 1992 to December 2021. The t-statistics with Newey and West (1987) adjusted standard errors are shown in parentheses.

	Intraday		Overnight		Intraday−Overnight (scaled)	Intraday+Overnight (scaled)
	(1)	(2)	(3)	(4)	(5)	(6)
CF RET	0.340		0.168		1.024	1.485
	(4.51)		(4.36)		(4.03)	(4.93)
CF Day		0.537		0.010	1.971	1.997
		(7.00)		(0.37)	(7.20)	(7.02)
CF Night		-0.304		0.439	-1.723	-0.519
		(-4.88)		(8.18)	(-7.56)	(-2.17)
Controls	√	√	√	√		
Intercept	0.857	0.842	0.663	0.672		
	(3.44)	(3.37)	(3.12)	(3.15)		
Avg. R^2(%)	5.494	5.953	3.477	3.783		
Avg. # Obs	2268	2268	2268	2268		

TABLE 6

Fama-MacBeth regressions: control for focal stocks' tug-of-war

This table reports the time-series averages of coefficients from monthly cross-sectional regressions. The dependent variable in the first two columns is the focal stock's subsequent intraday return (in percentage); the dependent variable in the third and fourth columns is the focal stock's overnight return in the following month (in percentage). Ret Day and Ret Night are the focal stock's own intraday return and overnight return in the past month, respectively. Other control variables are defined identically as in Table 5. The focal stock's past 1-month return (close-to-close) is excluded since Ret Day and Ret Night are included in regressions. Columns (5) and (6) report the scaled difference between and the scaled sum of the intraday coefficient$\times 24/6.5$ and the overnight coefficient$\times 24/17.5$. Independent variables are winsorized at 1% and 99% each month and standardized to have zero mean and unit variance. The sample period is from July 1992 to December 2021. The t-statistics with Newey and West (1987) adjusted standard errors are shown in parentheses.

	Intraday		Overnight		Intraday−Overnight (scaled)	Intraday+Overnight (scaled)
	(1)	(2)	(3)	(4)	(5)	(6)
CF RET	0.288		0.208		0.776	1.347
	(3.84)		(5.53)		(3.07)	(4.50)
CF Day		0.444		0.096	1.508	1.772
		(6.09)		(3.54)	(5.87)	(6.42)
CF Night		-0.225		0.347	-1.309	-0.356
		(-3.72)		(8.01)	(-6.22)	(-1.49)
Ret Day	√	√	√	√		
Ret Night	√	√	√	√		
Controls	√	√	√	√		
Intercept	0.834	0.822	0.693	0.697		
	(3.35)	(3.30)	(3.25)	(3.26)		
Avg. R^2(%)	6.534	6.906	5.678	5.873		
Avg. # Obs	2268	2268	2268	2268		

TABLE 7

Institutional investors' recognition and trading

This table reports results from panel regressions:

$$\Delta \text{BD}_{i,q+1} = \alpha + \beta_{Day}\text{CF Day}_{i,q} + \beta_{Night}\text{CF Night}_{i,q} + Controls_{i,q} + \varepsilon_{i,q+1}$$
$$\Delta \text{INST}_{i,q+1} = \alpha + \beta_{Day}\text{CF Day}_{i,q} + \beta_{Night}\text{CF Night}_{i,q} + Controls_{i,q} + \varepsilon_{i,q+1}$$

The dependent variable is the change in the breadth of institutional ownership (ΔBD, the first four columns) or the change in institutional ownership (ΔINST, the last four columns) measuring in the subsequent quarter. The main independent variables of interest are peer stocks' lagged intraday returns (CF Day) and overnight returns (CF Night). I control for the focal stock's own lagged intraday and overnight returns, past 11-month return, log of market capitalization, log of book-to-market ratio, and market beta. Market beta is included to control for the potential demand for leverage and is calculated using daily returns with a 12-month rolling window. The last row ($\beta_{Day} - \beta_{Night}$) reports the difference between the estimated coefficients on CF Day and CF Night. All independent variables are winsorized at 1% and 99% and normalized to have zero mean and unit variance each quarter. The t-statistics are reported using standard errors clustered on firm and quarter. The sample period is from 1992 to 2021.

	ΔBD				ΔINST			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CF RET	0.018	0.018			0.047	0.050		
	(4.03)	(3.91)			(2.04)	(2.09)		
CF Day			0.017	0.018			0.045	0.055
			(3.93)	(3.88)			(2.01)	(2.38)
CF Night			0.006	0.005			-0.009	-0.027
			(1.49)	(1.15)			(-0.42)	(-1.26)
Controls	√	√	√	√	√	√	√	√
Year-Quarter FE	√	√	√	√	√	√	√	√
Industry FE		√		√		√		√
N	262501	250384	262501	250384	262501	250384	262501	250384
Adj. R^2	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
$\beta_{Day} - \beta_{Night}$			0.011	0.013			0.054	0.082
			(2.89)	(3.27)			(2.11)	(3.19)

TABLE 8

Retail investors' attention and net purchase

This table reports results from panel regressions:

$$\text{Attention}_{i,t+1} = \alpha + \beta_{Day}|\text{CF Day}_{i,t}| + \beta_{Night}|\text{CF Night}_{i,t}| + Controls_{i,t} + \varepsilon_{i,t+1}$$
$$\text{Net purchase}_{i,t+1} = \alpha + \beta_{Day}\text{CF Day}_{i,t} + \beta_{Night}\text{CF Night}_{i,t} + Controls_{i,t} + \varepsilon_{i,t+1}$$

The dependent variable is the abnormal Google search volume (in percentage, the first four columns) or the net purchase of retail investors (in basis points, the last four columns) measuring in the subsequent month. In columns (1) to (4), the main independent variables of interest are the magnitude (absolute value) of peer stocks' close-to-close, intraday, and overnight returns; I control for the focal stock's absolute intraday and overnight returns, past 11-month return, log of market capitalization, log of book-to-market ratio, idiosyncratic volatility, and illiquidity. I further control for a battery of characteristics that potentially correlate with retail attention (Da et al., 2011), including institutional ownership, analyst coverage, the maximum daily return in the past month, the log of share price, and abnormal trading volume in the past month. In columns (5) to (8), the main independent variables of interest are peer stocks' close-to-close, intraday, and overnight returns; the corresponding control variables include the focal stock's past intraday and overnight returns, past 11-month return, log of market capitalization, log of book-to-market ratio, idiosyncratic volatility, and illiquidity. The last row ($\beta_{Day} - \beta_{Night}$) reports the difference between the estimated coefficients on peer stocks' intraday returns and overnight returns. All independent variables are winsorized at 1% and 99% and normalized to have zero mean and unit variance each month. The t-statistics are reported using standard errors clustered on firm and month. The sample period is from 2004 to 2020 for the first four columns and from 2007 to 2021 for the last four columns.

	Attention				Net purchase			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
|CF RET|	0.128	0.062						
	(0.71)	(0.32)						
|CF Day|			-0.273	-0.282				
			(-1.64)	(-1.59)				
|CF Night|			0.491	0.414				
			(2.75)	(2.12)				
CF RET					0.129	0.163		
					(2.53)	(3.27)		
CF Day							0.020	0.081
							(0.38)	(1.57)
CF Night							0.284	0.235
							(5.20)	(4.51)
Controls	√	√	√	√	√	√	√	√
Year-Month FE	√	√	√	√	√	√	√	√
Industry FE		√		√		√		√
N	401675	372736	401676	372737	353838	318166	353838	318166
Adj. R^2	0.05	0.05	0.05	0.05	0.02	0.02	0.02	0.02
$\beta_{Day} - \beta_{Night}$			-0.764	-0.696			-0.264	-0.154
			(-2.88)	(-2.50)			(-3.50)	(-2.13)

TABLE 9

Order imbalance

This table reports results from panel regressions:

$$\text{Order imbalance}_{i,t+1} = \alpha + \beta_{Day}\text{CF Day}_{i,t} + \beta_{Night}\text{CF Night}_{i,t} + Controls_{i,t} + \varepsilon_{i,t+1}$$

The dependent variable is the focal stock's order imbalance (in percentage) in the subsequent month, calculated by averaging daily order imbalance within the month. Daily order imbalance is computed based on the number of trades (Trade), trading volume (Volume), or dollar value (Value). The main independent variables of interest are peer stocks' intraday and overnight returns. Control variables include the focal stock's past intraday and overnight returns, past 11-month return, log of market capitalization, log of book-to-market ratio, idiosyncratic volatility, and illiquidity. The last row ($\beta_{Day} - \beta_{Night}$) reports the difference between the estimated coefficients on peer stocks' intraday returns and overnight returns. All independent variables are winsorized at 1% and 99% and normalized to have zero mean and unit variance each month. The t-statistics are reported using standard errors clustered on firm and month. The sample period is from 2007 to 2021.

	Retail order imbalance						Total order imbalance					
	Trade		Volume		Value		Trade		Volume		Value	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CF RET	0.129		0.147		0.147		0.047		0.057		0.057	
	(3.38)		(4.05)		(4.05)		(2.73)		(3.49)		(3.44)	
CF Day		0.036		0.043		0.042		0.048		0.046		0.045
		(0.94)		(1.17)		(1.16)		(2.85)		(2.84)		(2.74)
CF Night		0.249		0.263		0.265		-0.025		-0.010		-0.007
		(6.10)		(7.04)		(7.07)		(-1.30)		(-0.51)		(-0.34)
Controls	√	√	√	√	√	√	√	√	√	√	√	√
Year-Month FE	√	√	√	√	√	√	√	√	√	√	√	√
N	353810	353810	353810	353810	353810	353810	353824	353824	353824	353824	353824	353824
Adj. R^2	0.06	0.06	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.05	0.05
$\beta_{Day} - \beta_{Night}$		-0.213		-0.220		-0.223		0.073		0.056		0.052
		(-3.91)		(-4.38)		(-4.41)		(2.97)		(2.15)		(1.96)

TABLE 10

Aggregate fund flows and cross-firm tug-of-war

This table reports results from time-series regressions:

$$ToW_{t+1} = \alpha + \beta_{MF}^{ToW} MFFLOW_t + \beta_{HF}^{ToW} HFFLOW_t + Controls + \varepsilon_{t+1},$$

where the dependent variable (ToW_{t+1}) is the return of the cross-firm tug-of-war. Specifically, ToW_{t+1} represents the value-weighted intraday/overnight return of the high-minus-low portfolio formed by peer stocks' returns, comprising the four components depicted in Figure 1 and examined in Table 4: (1) Night-to-Night, the overnight return of the high-minus-low portfolio formed by CF Night; (2) Night-to-Day, the intraday return of the high-minus-low portfolio formed by CF Night; (3) Day-to-Night, the overnight return of the high-minus-low portfolio formed by CF Day; and (4) Day-to-Day, the intraday return of the high-minus-low portfolio formed by CF Day. The main independent variables of interest are aggregate mutual fund flow ($MFFLOW_t$) and aggregate hedge fund flow ($HFFLOW_t$) from the previous month. Fund flows are calculated following the methodology of Akbas et al. (2015). All regressions include controls for the lagged investor sentiment index (SENT) of Baker and Wurgler (2006), as Stambaugh, Yu, and Yuan (2012) show that many asset pricing anomalies become stronger following high-sentiment periods. Additionally, the lagged VIX index is included to account for the potential influences of market volatility and liquidity. Independent variables are standardized to have zero mean and unit variance. Other control variables include the contemporaneous returns of the six asset pricing factors of Fama and French (2015). To mitigate survivorship bias in hedge fund data, the sample period is from January 1994 to December 2021. The t-statistics with Newey and West (1987) adjusted standard errors are shown in parentheses.

	(1) Night-to-Night	(2) Night-to-Day	(3) Day-to-Night	(4) Day-to-Day
MFFLOW	0.939	-0.672	-0.166	-0.030
	(3.24)	(-2.05)	(-0.86)	(-0.09)
HFFLOW	-0.072	-0.347	-0.055	0.599
	(-0.35)	(-1.40)	(-0.25)	(2.56)
SENT	0.095	0.280	-0.200	0.153
	(0.60)	(0.79)	(-0.68)	(0.52)
VIX	0.414	-0.093	-0.175	0.247
	(1.40)	(-0.30)	(-0.76)	(0.82)
Controls	√	√	√	√
Intercept	1.563	-1.319	-0.289	0.869
	(5.05)	(-4.98)	(-1.39)	(3.13)
N	335	335	335	335

TABLE 11

The information content of peer stocks' intraday and overnight returns

This table reports results from panel regressions:

$$\text{Fundamental}_{i,q+1} = \alpha + \beta_{Day}\text{CF Day}_{i,q} + \beta_{Night}\text{CF Night}_{i,q} + Controls_{i,q} + \varepsilon_{i,q+1}$$

The dependent variables are one-quarter-ahead fundamentals (multiplied by 100), including (1) standardized unexpected earnings (SUE): unexpected earnings scaled by the standard deviation of unexpected earnings over the preceding eight quarters. The unexpected earnings are measured by year-over-year changes in quarterly earnings before extraordinary items; (2) return-on-assets (ROA): the net income before extraordinary items scaled by one-quarter-lagged total assets; (3) gross profitability (GP): the total revenue minus cost of goods sold divided by one-quarter-lagged total assets; (4) asset growth (AG): total assets divided by its value four quarters ago and then minus one; (5) sales growth (SG): quarterly sales divided by the four-quarter-lagged value, and then minus one; and (6) revenue growth (RG): quarterly total revenue divided by its value four quarters ago, then minus one. The main independent variables of interest are peer stocks' lagged intraday returns (CF Day) and overnight returns (CF Night). I control for the focal stock's own lagged intraday and overnight returns, past 11-month return, log of market capitalization, and log of book-to-market ratio. The last row ($\beta_{Day} - \beta_{Night}$) reports the difference between the estimated coefficients on peer stocks' intraday returns and overnight returns. The sample is restricted to firms with fiscal quarters ending in March, June, September, and December. Variables are winsorized at 1% and 99% each quarter, and independent variables are standardized cross-sectionally to have zero mean and unit variance. The sample ranges from 1992 to 2021. Standard errors are clustered by firm and quarter, and t-statistics are reported in parentheses.

	SUE		ROA		GP		AG		SG		RG	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CF Day	5.362	5.022	0.268	0.213	0.421	0.287	-0.362	-0.339	-0.291	-0.139	-0.281	-0.153
	(3.52)	(3.46)	(4.23)	(4.86)	(4.18)	(4.54)	(-0.54)	(-0.51)	(-0.63)	(-0.36)	(-0.60)	(-0.39)
CF Night	-4.876	-2.200	-0.676	-0.438	-0.894	-0.488	3.855	3.235	5.204	3.849	5.316	3.851
	(-3.80)	(-1.80)	(-9.97)	(-10.13)	(-9.96)	(-8.70)	(4.71)	(3.78)	(9.92)	(8.65)	(9.99)	(8.65)
Controls	√	√	√	√	√	√	√	√	√	√	√	√
Time FE	√	√	√	√	√	√	√	√	√	√	√	√
Industry FE		√		√		√		√		√		√
N	221344	209756	223222	211311	220953	210311	223096	211350	218788	208817	217286	208572
Adj. R^2	0.06	0.07	0.11	0.13	0.10	0.25	0.13	0.13	0.09	0.11	0.09	0.11
$\beta_{Day} - \beta_{Night}$	10.238	7.222	0.944	0.651	1.315	0.775	-4.217	-3.574	-5.495	-3.988	-5.597	-4.004
	(5.78)	(4.12)	(13.48)	(13.22)	(11.73)	(10.27)	(-5.82)	(-5.39)	(-8.53)	(-7.86)	(-8.64)	(-7.85)

Appendix to "Decoding Momentum Spillover Effects"

This Appendix provides additional empirical results omitted from the paper for the sake of brevity.

A. Summary

- Figure A1: Persistence of cross-firm tug-of-war
- Figure A2: Long-horizon returns
- Figure A3: Daily cross-firm tug-of-war
- Table A1 Definition of variables used in analysis
- Table A2: Non-retail order imbalance
- Table A3: Institutional flows
- Table A4: Lead-lag effects from alternative economic linkage settings
- Table A5: Intraday/overnight performance of alternative lead-lag settings
- Table A6: Portfolios using long signal formation horizons
- Table A7: Cross-firm tug-of-war: alternative opening price definition
- Table A8: Daily cross-firm tug-of-war
- Table A9: Summary statistics of information discreteness
- Table A10: Information discreteness: portfolio characteristics
- Table A11: Information discreteness and lead-lag returns relation
- Table A12: Burt and Hrdlicka (2021) decomposition of signals
- Table A13: Intensity of cross-firm tug-of-war and future returns

B. Results from additional lead-lag settings

Table A4 and Table A5 report long-short portfolio results based on alternative definitions of peer firms including the Fama-French 49 industry classification (INDFF), the three-digit SIC codes industry classification (INDSIC), the text-based industry classification (INDTIC), geographic links (GEO), technological links (TECH), and conglomerate firms (CONGLM). Table A4 examines lead-lag effects using the original 24-hour signal, the day signal, and the night signal; Table A5 examines future overnight and intraday returns. In each table, stocks are sorted into quintile portfolios based on peer firm signals, and equal-weighted portfolios are formed and held for one month.

To construct text-based industry signals, I first download the 10-K Text-based Industry Classifications data from the Hoberg-Phillips Data Library.[1] The data file contains the firm identifier (gvkey), year, and the corresponding industry classifications. I use the 50-industry classification (icode50) in this study. The dataset is merged to add the stock identifier (permno) of CRSP using the CCM link table provided by *Wharton Research Data Services* (WRDS). To form industry and geographic signals, for each firm, I calculate value-weighted (equal-weighted) average returns of all other stocks in the same industry (area) for the previous month. Similarly, the overnight return and intraday return are used in place of the gross return to create the day and night signals, respectively. The main results also hold when using the more granular text-based network industry classification, in which industry momentum variables are calculated as the similarity score-weighted average return of peer firms.

The patent data are provided by Kogan et al. (2017) and contain the patent-permno match

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

panel, the patent-level data, and the patent-CPC class match information.[2] Following Lee et al. (2019), each year, I calculate the pairwise technological closeness as the uncentered correlation of the patent distributions between all pairs of firms, where patent distributions are computed using a five-year rolling window. The monthly returns of technological links are then calculated as the technology closeness-weighted return of linked firms, assuming that the patent information becomes publicly available six months after the end of the year in which the patent is announced. The day and night TECH signals are calculated analogously.

Conglomerate firms are identified using COMPUSTAT segment files. Specifically, a firm is defined as a conglomerate (stand-alone) if it operates in more than one (only one) industry and the aggregate segment sales account for more than 80% of the total sales. Next, I calculate the value-weighted average returns of the stand-alone firms within each of the conglomerate firm's industry segments, where industries are defined using two-digit SIC codes. Then, a pseudo-conglomerate portfolio is constructed using stand-alone firms from the respective industries, weighted by the conglomerate firm's segment sales. The gross, intraday, and overnight returns of pseudo-conglomerate portfolios are calculated as conglomerate firms' signals. Following Cohen and Lou (2012), I impose at least a six-month lag between firm fiscal year-ends and portfolio formations.

[2] `https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data`

C. Additional robustness tests

C1. Cross-firm tug-of-war persistence

The tug-of-war pattern among connected firms builds on the investor heterogeneity hypothesis of Lou et al. (2019) and Lou et al. (2024). To the extent that overnight clientele's order flow is persistent, we are expected to see persistence in the cross-firm tug-of-war from peer firms' overnight returns. Meanwhile, if the cross-firm spillover of intraday returns is mainly driven by slow-moving arbitrage, then the continuation of daytime returns should be less persistent as prices are corrected.

Figure A1 presents how the cross-firm predictability using intraday and overnight returns evolves with the lag between the ranking period and the holding period. Consistently, the cross-firm tug-of-war from peer firms' overnight returns can persist for up to five years. The inter-firm, cross-period continuation of intraday returns, however, only persists for one month and becomes less stable for longer horizon lags.

C2. Signal formation period and investment horizons

This section examines the lead-lag returns relation using signals with longer horizon lags. I calculate day and night signals from co-analyst firms' returns over periods $[t-3, t-1]$, $[t-6, t-1]$, $[t-12, t-2]$, $[t-36, t-13]$, and $[t-60, t-13]$, respectively. Appendix Table A6 reports the predictability results. For connected-firm intraday returns, Panel A indicates that signals constructed from the past three months, six months, and one year (skipping the most recent month) still positively predict focal stocks' future returns, and the profitability of intraday momentum spillover decreases with longer signal formation horizons. For lags beyond one year, the intraday signal is not significantly associated with future returns. These findings are consistent with Ali and Hirshleifer (2020). For connected-firm overnight returns, Panel B of Table A6 shows no evidence of momentum spillovers. Overall, the result suggests that cross-predictability from intraday and overnight signals is not sensitive to the choice of reference horizon.

I also follow the methodology of Jegadeesh and Titman (1993) to calculate long-term strategy returns. Appendix Figure A2 shows the cumulative returns of equal- and value-weighted hedge portfolios based on CF Day and CF Night, respectively. The returns to strategies based on the intraday signal tend to drift upward in the long run, with a one-year cumulative return of up to 5%. However, the overnight signal is unable to positively predict future close-to-close returns for long investment horizons. The value-weighted returns of the CF Night strategy are close to zero across all horizons, and the equal-weighted returns even drift downward slightly. These findings are consistent with the main results of previous tests.

C3. Alternative opening price definition

Throughout the paper, I have used the opening price reported by CRSP to decompose returns into the intraday and overnight components. For robustness, I re-examine the cross-firm tug-of-war result by calculating the volume-weighted average price (VWAP) in the first 15-minute trading interval (9:30 am to 9:45 am) as the opening price. Using this alternative definition of opening price, I re-calculate intraday and overnight returns as well as the CF Day and CF Night signals. In a series of Fama-MacBeth regressions reported in Table A7, I show that CF Night consistently predicts focal stocks' subsequent overnight (intraday) returns with a positive (negative) sign; CF

Day remains a strong positive predictor of future intraday returns, while it exhibits only a minor relation with future overnight returns.

C4. Daily cross-firm tug-of-war

To examine return spillovers and my proposed mechanism more granularly, I investigate cross-predictability at the daily frequency. Each trading day and each focal stock, I calculate daily CF Day and daily CF Night by averaging connected firms' daily intraday returns and overnight returns, respectively. Quintile portfolios are formed each trading day based on these two daily signals. The daily CF Day (CF Night) strategy takes a long position in the top quintile and a short position in the bottom quintile. I calculate value-weighted strategy intraday and overnight returns over the next h trading days, with h ranging from 1 to 30. Portfolios are constructed following the approach of Jegadeesh and Titman (1993).

Appendix Figure A3 and Table A8 show that, over short horizons such as three trading days, CF Day positively predict both intraday and overnight returns. This result accords with recent work by Jones, Pyun, and Wang (2024), who suggest that due to extrapolative trading by retail investors, daily overnight returns correlate positively with lagged daytime and overnight returns. Over longer horizons up to 30 trading days, the relationship between CF Day and subsequent overnight returns turns negative and small in magnitude; the predictive ability of CF Day for intraday returns remain robust and strong. For daily CF Night strategy, the continuation of overnight returns occurs at a one-day horizon and remains persistent afterwards. The daytime reversal effect associated with the daily CF Night signal emerges slightly later (not fully on the next day open), presumably because immediate arbitrage is risky and costly for institutions. While aligning with the story proposed in this paper, the daily strategy results also provide further evidence on the generating process of cross-firm return predictability at high frequency.

C5. Information discreteness

An alternative interpretation for my baseline findings is that peer stocks' intraday returns are more *continuous* than overnight returns. Da et al. (2014) propose that investors tend to be inattentive to information arriving continuously in small amounts, whereas information arriving discretely in large amounts attracts more attention. Using the information discreteness (ID) measure of Da et al. (2014), Huang et al. (2022) find that the lead-lag returns relation is more pronounced for continuous signals. Thus, one might conjecture that investors perceive overnight returns to be more discrete than intraday returns, leading to the difference between CF Day and CF Night in the predictive power for future returns.

To test this explanation, I start by examining whether the intraday signal is more continuous than the overnight signal. I calculate information discreteness for the day signal and night signal, respectively, following the definition of Da et al. (2014):

$$ID_{i,t}^{P} = sign(CR_{i,t}^{P}) \times [\%neg_{i,t}^{P} - \%pos_{i,t}^{P}],\ P \in \{Day,\ Night\}\,.$$

In the above equation, $CR_{i,t}^{P}$ is the cumulative return of firm i's connected firm over the past month for period P, $sign(CR_{i,t}^{P})$ is the sign of $CR_{i,t}^{P}$, and $\%neg_{i,t}^{P}$ ($\%pos_{i,t}^{P}$) is the percentage of days during the past month with negative (positive) connected-firm returns.

Appendix Table A9 shows that the distribution properties of the intraday signal information discreteness (ID^{Day}) and the overnight signal information discreteness (ID^{Night}) are very similar, although ID^{Day} is slightly larger than ID^{Night} on average. Appendix Table A10 further confirms the similarity of ID distribution at the portfolio level. Then, I examine the pricing of peer stocks' intraday and overnight returns conditioning on ID. Appendix Table A11 reports the result of the lead-lag relation within each information discreteness level. Consistent with Da et al. (2014) and Huang et al. (2022), the predictive power of CF Day is weaker when returns arrive more discretely. However, CF Night still cannot predict future returns even for the most continuous signal group. In sum, while I cannot completely rule out the information discreteness hypothesis, the results suggest that this channel solely is unlikely to drive the main findings of this paper.

C6. The Burt and Hrdlicka (2021) decomposition

Burt and Hrdlicka (2021) define the *common* component of returns as the portion predicted by exposure to systematic pricing factors (including an estimated intercept), and label the unexplained residual the *news* component. Specifically, they regress monthly stock returns from $t-12$ to $t-1$ on a five-factor model, including the three factors of Fama and French (1996), the momentum factor of Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). Then, the predictable common component of stock i in month t is calculated by $\hat{\alpha}_{i,t-1} + \sum_{k=1}^{5} \hat{\beta}_{i,t-1}^{k} f_t^k$, where $\hat{\alpha}_{i,t-1}$ is the estimated intercept, $\hat{\beta}_{i,t-1}^{k}$ is the estimated exposure to factor k, and f_t^k is factor realization in month t. The news component is stock i's month t excess return minus the common component. Following their approach, I decompose each stock's monthly intraday and overnight returns into the common and the news components.[3] Then, I calculate averages of different components of

[3]In this analysis, I use standard close-to-close (total) factor returns. Untabulated results show that decomposing intraday (overnight) stock returns with factors' intraday (overnight) returns yields similar conclusions.

peer stock returns, thereby decomposing CF Day and CF Night into four constituents: CF Day *Common*, CF Day *News*, CF Night *Common*, and CF Night *News*.

In Appendix Table A12, I find that both components contribute to the main patterns documented in this paper. For CF Day, the *Common* component and the *News* component predict subsequent intraday returns equally well, whereas their correlations with subsequent overnight returns are both minimal in magnitude. For CF Night, the continuation of overnight returns and reversal of intraday returns are evident for both components. Moreover, the *Common* component of CF Night appears to generate stronger cross-firm tug-of-war than the *News* component. A potential interpretation is that commonality in CF Night serves as a proxy for retail invesor habitat, since retail investors typically exhibits preferences for certain stock characteristics (Huang, 2019; Balasubramaniam et al., 2023). Consequently, the focal stock's opening price tends to depart further from fundamentals when the *Common* component of CF Night predicts substantial unjustified demand from retail investors. In addition to implementing their approach and complementing their findings, my analysis also shares the view of Burt and Hrdlicka (2021) that investor underreaction alone may not fully characterize the return predictability pattern of economically connected firms.

C7. Tug-of-war intensity and future returns

I extend my analysis by studying the implication of cross-firm tug-of-war. Akbas et al. (2021) find that the monthly intensity of the daily tug-of-war, defined as the abnormal frequency of negative daytime reversal, is positively associated with future returns. They hypothesize that a prolonged tug-of-war reflects the overcorrection behavior of daytime arbitrageurs. It follows that stocks with intensive daytime reversals are underpriced because arbitrageurs underweight the information content of overnight returns and overweight the influence of noise traders. In the cross-predictability setting, evidence from previous sections suggests that there exists a strong negative relation between peer stocks' overnight returns and focal stocks' future intraday returns. Extending the logic of Akbas et al. (2021), one would expect that a more intensive cross-firm tug-of-war implies a higher future return of the focal stock.

I follow the method of Akbas et al. (2021) in measuring the intensity of a daily cross-firm tug-of-war. Specifically, a negative cross-firm daytime reversal is defined as a positive peer stock overnight return that is followed by a negative focal stock intraday return. Then, I calculate the ratio of the number of days with negative cross-firm daytime reversals each month, denoted by NR^C. The monthly abnormal intensity of a cross-firm tug-of-war, AB_NR^C, is defined as NR^C scaled by the average NR^C over the past 12 months. Appendix Table A13 reports the returns of portfolios formed by AB_NR^C, which shows that the intensity of a cross-firm tug-of-war is indeed a strong predictor of future returns. For example, the strategy of buying stocks in the top AB_NR^C decile and selling stocks in the bottom AB_NR^C decile generates a return of 82 basis points per month ($t = 5.47$). It thus supports the hypothesis that arbitrageurs notice overnight returns of peer stocks, and a more aggressive price overcorrection, represented by a high frequency of inter-firm daytime reversal, is positively associated with focal stocks' future returns.

FIGURE A1

Persistence of cross-firm tug-of-war

This figure reports value-weighted portfolio results using longer lags between the ranking month and the holding month. The dashed blue curve with circle markers represents using lagged peer stocks' overnight returns to predict the focal stock's overnight returns. The dashed orange curve with circle markers represents using lagged peer stocks' intraday returns to predict the focal stock's intraday returns. The dashed gray curve with square markers represents using lagged peer stocks' intraday returns to predict the focal stock's overnight returns. The dashed green curve with square markers represents using lagged peer stocks' overnight returns to predict the focal stock's intraday returns. The sample period is from July 1992 to December 2021.

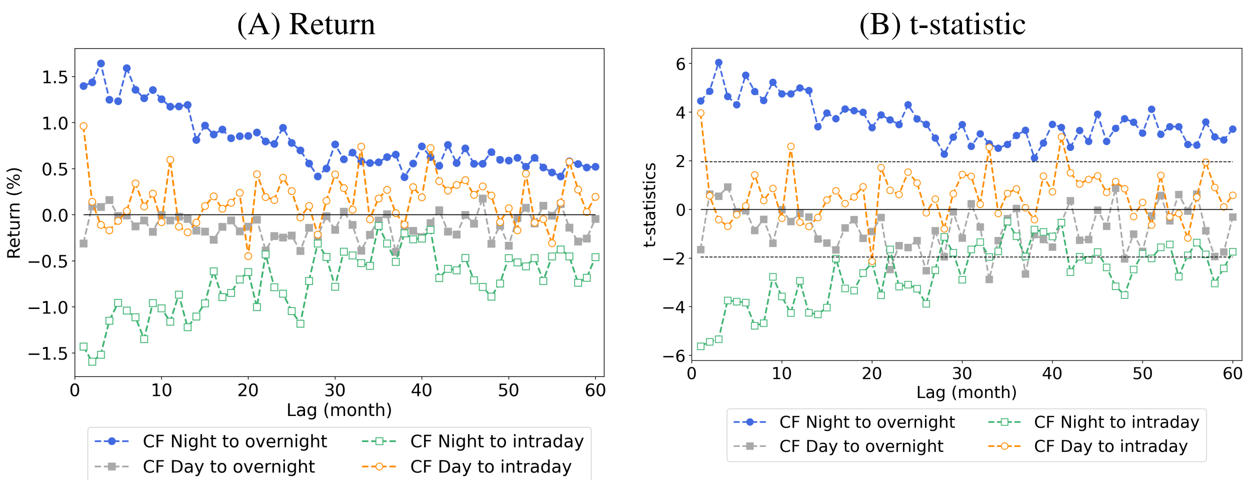

FIGURE A2

Long-horizon returns

This figure shows the cumulative close-to-close returns of trading strategies based on CF Day (orange lines) and CF Night (blue lines), respectively. Equal-weighted (solid and dash-dotted lines) and value-weighted (dashed and dotted lines) returns are calculated following the methodology of Jegadeesh and Titman (1993).

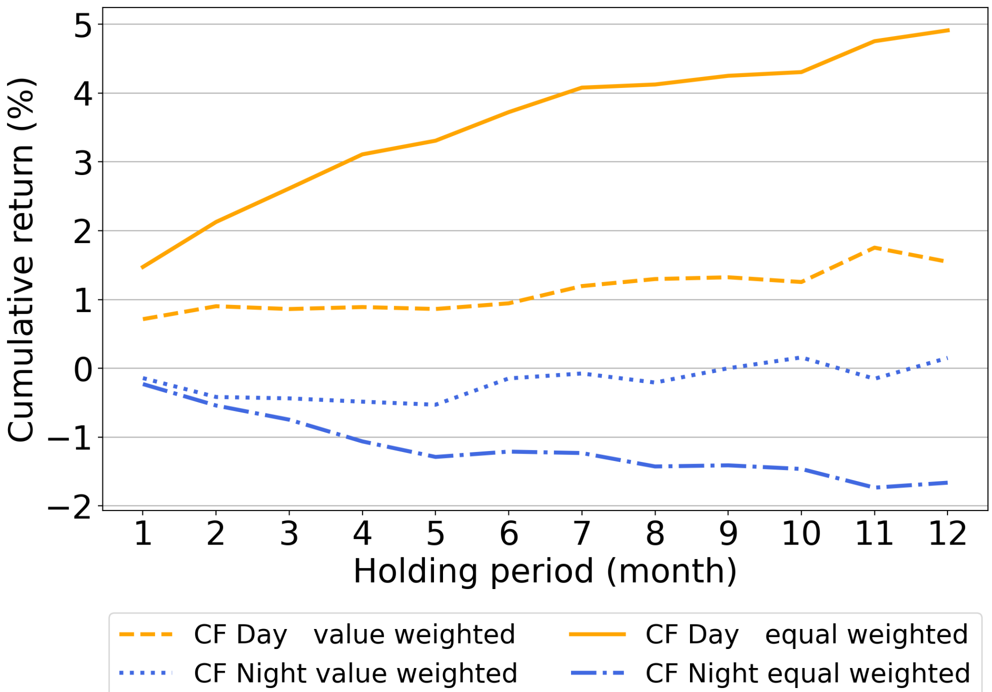

FIGURE A3

Daily cross-firm tug-of-war

This figure reports intraday and overnight returns (in basis points) of strategies based on daily CF Day and daily CF Night. Portfolios are constructed following the approach of Jegadeesh and Titman (1993). The shaded areas represent the 95% confidence intervals. The sample period is from July 1992 to December 2021.

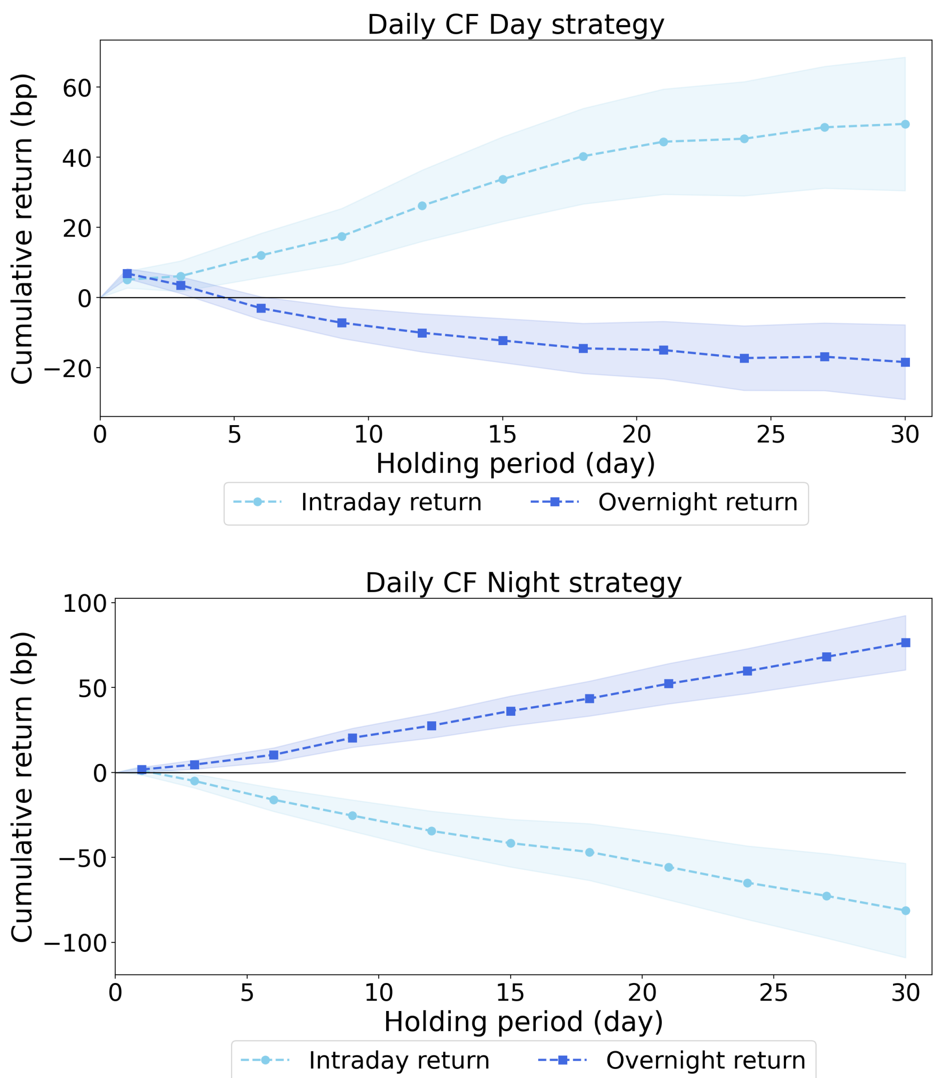

TABLE A1

Variable definition

Variable	Explanation	Definition
CF RET	Connected-firm portfolio close-to-close return (Ali and Hirshleifer, 2020)	Weighted average of peer stocks' monthly close-to-close returns: CF $\text{RET}_{i,t} = \frac{1}{\sum_{j=1}^{N_{i,t}} n_{i,j}} \sum_{j=1}^{N_{i,t}} n_{i,j} \, \text{Ret}_{j,t}$, where $n_{i,j}$ is the number of shared analysts, $N_{i,t}$ is the number of connected peers, and $\text{Ret}_{j,t}$ is the close-to-close monthly return of peer stock j in month t. Each month, two stocks are defined as connected peers if at least one analyst covered both stocks in the previous 12 months (Ali and Hirshleifer, 2020)
CF Day	Connected-firm portfolio intraday return	Weighted average of peer stocks' monthly intraday returns: CF $\text{Day}_{i,t} = \frac{1}{\sum_{j=1}^{N_{i,t}} n_{i,j}} \sum_{j=1}^{N_{i,t}} n_{i,j} \left(1 + r_{j,t}^{\text{Day}}\right)$, with $r_{j,t}^{\text{Day}}$ defined below
CF Night	Connected-firm portfolio overnight return	Weighted average of peer stocks' monthly overnight returns: CF $\text{Night}_{i,t} = \frac{1}{\sum_{j=1}^{N_{i,t}} n_{i,j}} \sum_{j=1}^{N_{i,t}} n_{i,j} \left(1 + r_{j,t}^{\text{Night}}\right)$, with $r_{j,t}^{\text{Night}}$ defined below
Ret CC	Monthly close-to-close total return for the focal stock	Standard close-to-close monthly return reported in CRSP
Ret Day	Monthly cumulative intraday return for the focal stock	Intraday return on day s defined as: $r_{i,s}^{\text{Day}} = (P_{i,s}^{\text{close}} - P_{i,s}^{\text{open}})/P_{i,s}^{\text{open}}$; month t cumulative defined as: $r_{i,t}^{Day} = \Pi_{s=1}^{S_{i,t}}(1 + r_{i,s}^{Day}) - 1$, where $S_{i,t}$ is the number of trading days of stock i in month t
Ret Night	Monthly cumulative overnight return for the focal stock	Overnight return on day s defined as: $r_{i,s}^{Night} = \frac{1+r_{i,s}^{close-to-close}}{1+r_{i,s}^{Day}} - 1$; month t cumulative defined as: $r_{i,t}^{Night} = \Pi_{s=1}^{S_{i,t}}(1 + r_{i,s}^{Night}) - 1$
ΔBD	Institutional recognition (Chen et al., 2002; Lehavy and Sloan, 2008)	Quarterly change in the breadth of institutional ownership: $\Delta\text{BD}_{i,q} = \frac{Num_{i,q} - Num_{i,q-1}}{TotalNum_{q-1}}$, where $Num_{i,q}$ and $Num_{i,q-1}$ are the number of 13-F filers holding stock i during quarter q and quarter $q-1$, respectively; $TotalNum_{q-1}$ is the total number of 13-F filers in quarter $q-1$
ΔINST	Institutional trading (Edelen et al., 2016)	Quarterly change in 13-F institutional ownership, winsorized per Nagel (2005)
Retail attention	Abnormal Google search volume (Da et al., 2011)	The log difference between the Google search volume in the current month and the average of Google search volume over the past year
Retail net purchase	Net retail trading scaled by shares outstanding (McLean et al., 2025)	Daily retail buys volume minus retail sells volume, scaled by shares outstanding, aggregated to month. Retail trades are identified based on the Boehmer et al. (2021) algorithm

(*Continued*)

Variable	Explanation	Definition
Total trade imbalance	Order imbalance based on the number of trades	Daily order imbalance calculated by $\frac{\#\text{Total buy trades} - \#\text{Total sell trades}}{\#\text{Total buy trades} + \#\text{Total sell trades}}$; Then average within the month
Total volume imbalance	Order imbalance based on shares traded	Daily order imbalance calculated by $\frac{\text{Total buy volume} - \text{Total sell volume}}{\text{Total buy volume} + \text{Total sell volume}}$; Then average within the month
Total value imbalance	Order imbalance based on the dollar value of trades	Daily order imbalance calculated by $\frac{\$\,\text{Total buy} - \$\,\text{Total sell}}{\$\,\text{Total buy} + \$\,\text{Total sell}}$; Then average within the month
Retail trade imbalance	Order imbalance based on the number of retail trades	Daily order imbalance calculated by $\frac{\#\text{Retail buy trades} - \#\text{Retail sell trades}}{\#\text{Retail buy trades} + \#\text{Retail sell trades}}$; Then average within the month
Retail volume imbalance	Order imbalance based on shares of retail trades	Daily order imbalance calculated by $\frac{\text{Retail buy volume} - \text{Retail sell volume}}{\text{Retail buy volume} + \text{Retail sell volume}}$; Then average within the month
Retail value imbalance	Order imbalance based on the dollar value of retail trades	Daily order imbalance calculated by $\frac{\$\,\text{Retail buy} - \$\,\text{Retail sell}}{\$\,\text{Retail buy} + \$\,\text{Retail sell}}$; Then average within the month
MFFLOW	Aggregate mutual fund flow (Akbas et al., 2015)	$\text{MFFLOW}_t = \frac{\sum_{i=1}^{N}\left[TNA_{i,t} - TNA_{i,t-1}(1+MRET_{i,t})\right]}{\sum_{i=1}^{N} TNA_{i,t-1}}$, where $TNA_{i,t}$ and $MRET_{i,t}$ denote the total net asset and the net-of-fee return, respectively, of a mutual fund
HFFLOW	Aggregate hedge fund flow (Akbas et al., 2015)	$\text{HFFLOW}_t = \frac{\sum_{i=1}^{N}\left[TNA_{i,t} - TNA_{i,t-1}(1+HRET_{i,t})\right]}{\sum_{i=1}^{N} TNA_{i,t-1}}$, where $TNA_{i,t}$ and $HRET_{i,t}$ denote the total net asset and the net-of-fee return, respectively, of a hedge fund
SUE	Standardized unexpected earnings	Unexpected earnings scaled by its standard deviation over the eight preceding quarters. Unexpected earnings are year-over-year changes in quarterly income before extraordinary items (item ibq)
ROA	Return-on-assets	Income before extraordinary items (item ibq) divided by 1-quarter-lagged total assets (item atq)
GP	Gross profitability	Total revenue (item revtq) minus cost of goods sold (item cogsq) divided by 1-quarter-lagged total assets (atq)
AG	Asset growth	Quarterly total assets (item atq) divided by its value four quarters ago, then minus one
SG	Sales growth	Quarterly sales (item saleq) divided by its value four quarters ago, then minus one
RG	Revenue growth	Quarterly total revenue (item revtq) divided by its value four quarters ago, then minus one

TABLE A2

Non-retail order imbalance

This table reports results from panel regressions:

$$\text{Order imbalance}_{i,t+1} = \alpha + \beta_{Day}\text{CF Day}_{i,t} + \beta_{Night}\text{CF Night}_{i,t} + Controls_{i,t} + \varepsilon_{i,t+1}$$

The dependent variable is the focal stock's non-retail order imbalance (in percentage) in the subsequent month, calculated by averaging daily non-retail order imbalance within the month. For each stock and each day, non-retail trades are defined as total trades minus retail trades where retail trades are identified using the Boehmer et al. (2021) algorithm. Then, daily non-retail order imbalance is computed based on the number of trades (Trade), trading volume (Volume), or dollar value (Value). The main independent variables of interest are peer stocks' intraday and overnight returns. Control variables include the focal stock's past intraday and overnight returns, past 11-month return, log of market capitalization, log of book-to-market ratio, idiosyncratic volatility, and illiquidity. The last row ($\beta_{Day} - \beta_{Night}$) reports the difference between the estimated coefficients on peer stocks' intraday returns and overnight returns. All independent variables are winsorized at 1% and 99% and normalized to have zero mean and unit variance each month. The t-statistics are reported using standard errors clustered on firm and month. The sample period is from 2007 to 2021.

	Non-retail order imbalance					
	Trade		Volume		Value	
	(1)	(2)	(3)	(4)	(5)	(6)
CF RET	0.044		0.051		0.051	
	(2.46)		(2.94)		(2.92)	
CF Day		0.046		0.046		0.044
		(2.63)		(2.64)		(2.52)
CF Night		-0.033		-0.030		-0.025
		(-1.71)		(-1.39)		(-1.16)
Controls	√	√	√	√	√	√
Year-Month FE	√	√	√	√	√	√
N	353808	353808	353807	353807	353808	353808
Adj. R^2	0.04	0.04	0.05	0.05	0.05	0.05
$\beta_{Day} - \beta_{Night}$		0.079		0.076		0.069
		(3.11)		(2.64)		(2.40)

TABLE A3

Institutional trading flows

This table reports results from panel regressions:

$$\text{Institutional flow}_{i,t+1} = \alpha + \beta_{Day}\text{CF Day}_{i,t} + \beta_{Night}\text{CF Night}_{i,t} + Controls_{i,t} + \varepsilon_{i,t+1}$$

The dependent variable is the focal stock's institutional trading flow (in basis points) in the subsequent month, calculated by averaging daily institutional flows within the month. Daily institutional flows for individual stocks are constructed by Campbell et al. (2009) using a regression-based approach. Specifically, Campbell et al. (2009) estimate a function mapping trades of different sizes into implied changes in institutional ownership. In the first two columns, daily institutional flows are calculated based on the mapping function estimated over the whole sample. In the last two columns, daily institutional flows are calculated based on an expanding window rolling estimation of the mapping function. The main independent variables of interest are peer stocks' intraday and overnight returns. Control variables include the focal stock's past intraday and overnight returns, past 11-month return, log of market capitalization, log of book-to-market ratio, idiosyncratic volatility, and illiquidity. The last row ($\beta_{Day} - \beta_{Night}$) reports the difference between the estimated coefficients on peer stocks' intraday returns and overnight returns. All independent variables are winsorized at 1% and 99% and normalized to have zero mean and unit variance each month. The t-statistics are reported using standard errors clustered on firm and month. The sample is restricted to NYSE stocks and ranges from 1993 to 2000.

	In-sample flows		Rolling out-of-sample flows	
	(1)	(2)	(3)	(4)
CF RET	0.039		0.040	
	(1.51)		(1.38)	
CF Day		0.069		0.066
		(2.61)		(2.23)
CF Night		-0.073		-0.048
		(-2.50)		(-1.35)
Controls	√	√	√	√
Year-Month FE	√	√	√	√
N	113116	113116	85224	85224
Adj. R^2	0.07	0.07	0.06	0.06
$\beta_{Day} - \beta_{Night}$		0.142		0.114
		(4.04)		(2.55)

TABLE A4

Lead-lag effects from alternative economic linkage settings

This table reports long-short portfolio results by sorting stocks based on peer firms' return signals. Peer firms are identified using the Fama-French 49 industry classification (INDFF), the three-digit SIC codes industry classification (INDSIC), the text-based industry classification (INDTIC), geographic links (GEO), technological links (TECH), and conglomerate firms (CONGLM), respectively. Portfolios are equal weighted, and the table presents excess returns in Panel A, four-factor alphas of Carhart (1997) in Panel B, and seven-factor alphas in Panel C. The sample period is from July 1992 to December 2021. The t-statistics with Newey and West (1987) adjusted standard errors are shown in parentheses.

Panel A. Excess return						
Signal	INDFF	INDSIC	INDTIC	GEO	TECH	CONGLM
24-hour	0.741	0.853	0.964	0.439	0.572	0.340
	(3.17)	(3.77)	(3.71)	(3.12)	(1.75)	(2.04)
Day	0.677	0.807	0.849	0.315	0.500	0.314
	(3.68)	(4.52)	(4.65)	(3.43)	(2.09)	(2.42)
Night	-0.002	0.039	0.175	-0.026	0.083	0.106
	(-0.01)	(0.21)	(0.71)	(-0.20)	(0.30)	(0.69)
Panel B. Carhart alpha						
Signal	INDFF	INDSIC	INDTIC	GEO	TECH	CONGLM
24-hour	0.746	0.886	0.922	0.506	0.617	0.394
	(3.86)	(4.56)	(4.19)	(4.03)	(2.35)	(2.47)
Day	0.746	0.890	0.909	0.436	0.630	0.387
	(3.86)	(4.89)	(4.67)	(4.54)	(3.04)	(2.85)
Night	-0.137	-0.124	0.017	-0.144	-0.066	-0.011
	(-0.88)	(-0.87)	(0.08)	(-1.64)	(-0.34)	(-0.07)
Panel C. Seven-factor alpha						
Signal	INDFF	INDSIC	INDTIC	GEO	TECH	CONGLM
24-hour	0.998	1.110	1.230	0.614	0.777	0.525
	(5.38)	(5.87)	(5.02)	(4.66)	(2.69)	(3.77)
Day	0.843	0.984	1.063	0.434	0.699	0.450
	(5.20)	(6.03)	(5.31)	(4.51)	(3.02)	(3.58)
Night	0.148	0.109	0.324	0.051	0.272	0.115
	(0.80)	(0.82)	(1.52)	(0.55)	(1.28)	(0.74)

TABLE A5

Intraday/overnight performance of alternative lead-lag settings

This table reports long-short portfolio results by sorting stocks based on peer firms' return signals. Peer firms are identified using the Fama-French 49 industry classification (INDFF), the three-digit SIC codes industry classification (INDSIC), the text-based industry classification (INDTIC), geographic links (GEO), technological links (TECH), and conglomerate firms (CONGLM), respectively. For each signal, I separately track one-month future intraday/overnight returns of portfolios. The equal-weighted returns of buying the top signal quintile stocks and selling the bottom signal quintile stocks are presented. The sample period is from July 1992 to December 2021. The t-statistics with Newey and West (1987) adjusted standard errors are shown in parentheses.

Panel A. Intraday returns (excess return)							Panel B. Intraday returns (seven-factor alpha)						
Signal	INDFF	INDSIC	INDTIC	GEO	TECH	CONGLM	Signal	INDFF	INDSIC	INDTIC	GEO	TECH	CONGLM
24-hour	0.473	0.584	0.601	0.277	0.166	0.210	24-hour	0.650	0.740	0.757	0.379	0.308	0.340
	(3.37)	(4.08)	(3.82)	(3.14)	(0.83)	(1.52)		(4.94)	(5.40)	(4.20)	(3.84)	(1.63)	(2.78)
Day	0.674	0.886	0.913	0.438	0.785	0.374	Day	0.794	1.006	1.059	0.507	0.913	0.447
	(4.66)	(6.10)	(5.56)	(4.69)	(4.21)	(3.15)		(5.31)	(6.93)	(5.41)	(5.18)	(4.76)	(3.67)
Night	-0.515	-0.689	-0.595	-0.414	-1.039	-0.311	Night	-0.434	-0.690	-0.525	-0.354	-0.896	-0.299
	(-3.17)	(-4.76)	(-2.79)	(-4.10)	(-5.69)	(-2.57)		(-2.76)	(-4.99)	(-2.45)	(-4.22)	(-5.63)	(-2.19)
Panel C. Overnight returns (excess return)							Panel D. Overnight returns (seven-factor alpha)						
Signal	INDFF	INDSIC	INDTIC	GEO	TECH	CONGLM	Signal	INDFF	INDSIC	INDTIC	GEO	TECH	CONGLM
24-hour	0.253	0.243	0.347	0.119	0.333	0.110	24-hour	0.339	0.343	0.449	0.177	0.384	0.150
	(1.67)	(1.75)	(1.88)	(1.12)	(1.76)	(1.26)		(2.48)	(2.83)	(2.63)	(1.78)	(2.19)	(1.85)
Day	-0.049	-0.132	-0.128	-0.170	-0.343	-0.090	Day	0.013	-0.059	-0.062	-0.134	-0.287	-0.035
	(-0.46)	(-1.23)	(-1.12)	(-2.23)	(-2.11)	(-1.09)		(0.12)	(-0.65)	(-0.56)	(-1.80)	(-1.76)	(-0.46)
Night	0.634	0.838	0.919	0.457	1.178	0.460	Night	0.697	0.904	0.986	0.479	1.230	0.448
	(3.64)	(4.76)	(3.86)	(4.33)	(6.16)	(5.13)		(3.99)	(5.11)	(4.12)	(4.40)	(6.44)	(5.20)

TABLE A6

Portfolios using long signal formation horizons

This table reports one-sort portfolio results by sorting stocks based on return signals with long horizon lags. For each type of connected-firm portfolio return (intraday or overnight), the corresponding signals are computed using returns over the past 3 months ($[t-3, t-1]$), 6 months ($[t-6, t-1]$), one year ($[t-12, t-2]$), 24 months ($[t-36, t-13]$), and 48 months ($[t-60, t-13]$). Portfolios are equal weighted and held for one month. I calculate returns and alphas of High-Low strategies using the four-factor model (Carhart, 1997) and the seven-factor model. The sample period is from July 1992 to December 2021. The t-statistics with Newey and West (1987) adjusted standard errors are shown in parentheses.

Panel A. Intraday return signal								
	Low	2	3	4	High	High-Low	Carhart alpha	FF7 alpha
$[t-3, t-1]$	0.096	0.596	0.852	1.134	1.542	1.445	1.574	1.482
	(0.22)	(1.89)	(3.02)	(3.95)	(4.48)	(4.55)	(5.65)	(4.89)
$[t-6, t-1]$	0.086	0.702	0.835	1.064	1.373	1.287	1.264	1.228
	(0.20)	(2.19)	(2.94)	(3.77)	(4.05)	(4.80)	(5.84)	(5.39)
$[t-12, t-2]$	0.327	0.779	0.917	0.955	1.148	0.821	0.679	0.454
	(0.75)	(2.33)	(3.19)	(3.26)	(3.56)	(3.11)	(3.38)	(2.37)
$[t-36, t-13]$	0.826	0.881	0.806	0.797	0.862	0.036	0.368	0.104
	(1.80)	(2.54)	(2.46)	(2.44)	(2.70)	(0.12)	(1.46)	(0.41)
$[t-60, t-13]$	0.644	0.824	0.805	0.822	0.892	0.248	0.497	0.231
	(1.34)	(2.11)	(2.38)	(2.40)	(2.68)	(0.92)	(2.05)	(1.03)
Panel B. Overnight return signal								
	Low	2	3	4	High	High-Low	Carhart alpha	FF7 alpha
$[t-3, t-1]$	0.975	0.912	0.852	0.920	0.561	-0.414	-0.758	-0.249
	(3.30)	(3.24)	(2.88)	(2.62)	(1.22)	(-1.15)	(-2.96)	(-1.18)
$[t-6, t-1]$	0.897	0.886	0.849	0.855	0.574	-0.323	-0.691	-0.171
	(3.17)	(3.09)	(2.81)	(2.35)	(1.23)	(-0.86)	(-2.92)	(-0.89)
$[t-12, t-2]$	0.882	0.931	0.840	0.860	0.614	-0.267	-0.693	-0.061
	(3.04)	(3.22)	(2.71)	(2.29)	(1.29)	(-0.69)	(-2.98)	(-0.33)
$[t-36, t-13]$	1.026	0.958	0.831	0.799	0.559	-0.466	-0.799	-0.170
	(3.49)	(3.05)	(2.42)	(1.98)	(1.15)	(-1.17)	(-3.33)	(-0.91)
$[t-60, t-13]$	0.905	0.838	0.802	0.850	0.592	-0.314	-0.673	-0.037
	(3.01)	(2.41)	(2.13)	(1.94)	(1.16)	(-0.74)	(-2.91)	(-0.23)

TABLE A7

Cross-firm tug-of-war: alternative opening price definition

This table reports estimated coefficients from Fama-MacBeth regressions. To calculate intraday and overnight returns, the opening price is measured using the volume-weighted average price (VWAP) in the first 15-minute interval of trading (9:30 am to 9:45 am). The dependent variable in the first two columns is the focal stock's subsequent intraday return (in percentage); the dependent variable in the third and fourth columns is the focal stock's overnight return in the following month (in percentage). Ret CC, Ret Day, and Ret Night are the focal stock's own close-to-close return, intraday return, and overnight return in the past month, respectively. Other control variables are defined identically as in Table 5. The last four columns report the scaled difference between and the scaled sum of the intraday coefficient$\times 24/6.5$ and the overnight coefficient$\times 24/17.5$. Independent variables are winsorized at 1% and 99% each month and standardized to have zero mean and unit variance. Due to the availability of TAQ data, the sample period is from January 1993 to December 2014. The t-statistics with Newey and West (1987) adjusted standard errors are shown in parentheses.

	Intraday		Overnight		Intraday−Overnight (scaled)		Intraday+Overnight (scaled)	
	(1)	(2)	(3)	(4)	(1)−(3)	(2)−(4)	(1)+(3)	(2)+(4)
CF Day	0.534	0.440	0.044	0.135	1.912	1.438	2.033	1.809
	(6.08)	(5.22)	(1.26)	(3.71)	(6.12)	(4.87)	(5.93)	(5.43)
CF Night	-0.327	-0.219	0.513	0.382	-1.912	-1.333	-0.505	-0.284
	(-4.50)	(-3.18)	(8.52)	(7.94)	(-6.78)	(-5.34)	(-1.80)	(-1.03)
Ret CC	√		√					
Ret Day		√		√				
Ret Night		√		√				
Controls	√	√	√	√				
Intercept	0.827	0.806	0.595	0.627				
	(3.18)	(3.08)	(2.55)	(2.65)				
Avg. R^2(%)	5.832	6.735	3.857	5.877				
Avg. # Obs	2355	2352	2355	2352				

TABLE A8

Daily cross-firm tug-of-war

This table reports cumulative returns (in basis points) of trading strategies formed by daily CF Day and daily CF Night. Each trading day, connected firms are identified using the shared analyst coverage (Ali and Hirshleifer, 2020) information as of the end of the previous month. Daily CF Day and daily CF Night are average daily and overnight returns of connected-peer firms, respectively. Strategy returns with a holding period of K trading days are calculated following the method of Jegadeesh and Titman (1993). The sample period is from July 1992 to December 2021. The t-statistics with Newey and West (1987) adjusted standard errors are shown in parentheses.

Holding period (K)	Daily CF Day strategy		Daily CF Night strategy	
	Intraday return	Overnight return	Intraday return	Overnight return
1	5.09	6.85	1.16	1.73
	(4.18)	(9.56)	(0.87)	(2.47)
3	6.10	3.55	-5.01	4.63
	(2.75)	(2.93)	(-2.39)	(3.42)
6	12.02	-3.06	-16.03	10.37
	(3.74)	(-1.83)	(-4.59)	(4.94)
9	17.48	-7.19	-25.40	20.43
	(4.34)	(-3.17)	(-5.40)	(7.15)
12	26.17	-10.04	-34.42	27.58
	(5.05)	(-3.62)	(-5.79)	(7.47)
15	33.72	-12.26	-41.59	36.22
	(5.48)	(-3.83)	(-5.81)	(8.06)
18	40.27	-14.49	-46.83	43.53
	(5.80)	(-3.98)	(-5.50)	(8.31)
21	44.41	-14.97	-55.63	52.27
	(5.80)	(-3.58)	(-5.63)	(8.64)
24	45.25	-17.25	-64.91	59.72
	(5.45)	(-3.68)	(-5.87)	(8.86)
27	48.51	-16.87	-72.66	68.09
	(5.48)	(-3.43)	(-5.73)	(9.16)
30	49.46	-18.39	-81.25	76.42
	(5.10)	(-3.39)	(-5.74)	(9.36)

TABLE A9

Summary statistics of information discreteness

This table reports summary statistics of information discreteness variables. Each month, I calculate daily returns of the connected-firm portfolio based on intraday returns and overnight returns, respectively. Then, I compute the information discreteness of the intraday signal (ID^{Day}) and the overnight signal (ID^{Night}) based on the definition of Da et al. (2014). The table presents the time-series average of cross-sectional distributions of ID^{Day}, ID^{Night}, and their difference ($ID^{Day} - ID^{Night}$). The sample period is from July 1992 to December 2021.

	Mean	Median	Std.Dev	Min	P25	P75	Max
ID^{Day}	-0.164	-0.161	0.164	-0.703	-0.270	-0.053	0.353
ID^{Night}	-0.178	-0.176	0.174	-0.781	-0.290	-0.061	0.383
$ID^{Day} - ID^{Night}$	0.014	0.011					

TABLE A10

Information discreteness: portfolio characteristics

This table reports the average information discreteness (ID) of portfolios sorted by ID and peer firms' return signal. Each month, stocks are independently sorted into three groups by ID and five groups by return signal. Then, I calculate the mean ID of each portfolio and take time-series averages. Panel A and Panel B present results based on peer stocks' intraday returns and overnight returns, respectively. The sample period is from July 1992 to December 2021.

Panel A. Intraday return signal

	Low	2	3	4	High
ID^{Day} 1	-0.312	-0.280	-0.279	-0.289	-0.323
ID^{Day} 2	-0.164	-0.158	-0.159	-0.165	-0.174
ID^{Day} 3	-0.022	-0.028	-0.032	-0.034	-0.037

Panel B. Overnight return signal

	Low	2	3	4	High
ID^{Night} 1	-0.313	-0.288	-0.293	-0.314	-0.373
ID^{Night} 2	-0.166	-0.161	-0.170	-0.183	-0.197
ID^{Night} 3	-0.010	-0.027	-0.038	-0.048	-0.054

TABLE A11

Information discreteness and lead-lag returns relation

This table reports double-sorted portfolios by information discreteness (ID) and peer firms' return signal. Each month, stocks are independently sorted into three groups by ID and five groups by return signal. Then, value-weighted returns of the resulting 3×5 portfolios in the next month are calculated. I also report the return spread between extreme quintile portfolios (High-Low) within each ID group, as well as the corresponding seven-factor alpha. Panel A and Panel B present results based on peer stocks' intraday returns and overnight returns, respectively. The sample period is from July 1992 to December 2021. The t-statistics with Newey and West (1987) adjusted standard errors are shown in parentheses.

Panel A. Intraday return signal							
	Low	2	3	4	High	High-Low	FF7 alpha
ID^{Day} 1	-0.03	0.81	0.74	0.93	1.04	1.08	1.48
	(-0.09)	(3.13)	(2.84)	(3.53)	(3.58)	(2.97)	(4.47)
ID^{Day} 2	0.33	0.82	0.70	0.96	1.09	0.76	1.05
	(0.99)	(3.25)	(2.69)	(3.78)	(3.71)	(2.48)	(3.49)
ID^{Day} 3	0.76	0.93	0.80	1.11	1.37	0.62	1.00
	(2.06)	(3.38)	(3.04)	(4.03)	(3.60)	(1.61)	(2.73)
Panel B. Overnight return signal							
	Low	2	3	4	High	High-Low	FF7 alpha
ID^{Night} 1	0.94	0.70	1.00	0.47	0.83	-0.10	0.13
	(3.55)	(2.95)	(4.32)	(1.65)	(2.10)	(-0.26)	(0.42)
ID^{Night} 2	0.87	0.83	0.79	0.65	0.55	-0.32	-0.20
	(3.60)	(3.60)	(3.31)	(2.47)	(1.28)	(-0.88)	(-0.62)
ID^{Night} 3	1.04	0.73	0.76	0.92	0.38	-0.65	-0.28
	(3.66)	(2.83)	(2.90)	(2.77)	(0.73)	(-1.39)	(-0.74)

TABLE A12

Burt and Hrdlicka (2021) decomposition of signals

This table reports estimated coefficients from Fama-MacBeth regressions. The dependent variable (in percentage) in the first three columns is the focal stock's subsequent close-to-close return, intraday return, and overnight return, respectively. Following Burt and Hrdlicka (2021), I regress each individual stock i's monthly returns (intraday or overnight) using observations from $t-12$ to $t-1$ on a five-factor model, including the three factors of Fama and French (1996), the momentum factor of Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). Each regression yields estimated intercept $\hat{\alpha}_{i,t-1}$ and factor exposures $\{\hat{\beta}^k_{i,t-1}\}^5_{k=1}$. Then, I decompose stock i's month t return (intraday or overnight) into the *Common* and the *News* components. Specifically, the *Common* part is the estimated intercept plus beta times factor realizations in t: $\hat{\alpha}_{i,t-1} + \sum^5_{k=1} \hat{\beta}^k_{i,t-1} f^k_t$. The *News* component is simply month t's return minus the common part. I conduct this decomposition each stock-month, and for intraday and overnight returns, separately. Then, I calculate peer stocks' average returns, which represents decomposition of the original signals into four variables: (1) CF Day *Common*; (2) CF Day *News*; (3) CF Night *Common*; and (4) CF Night *News*. In all Fama-MacBeth regressions, I control for the focal stock's own intraday return (Ret Day) and overnight return (Ret Night) in the past month. Other control variables are defined identically as in Table 5. The last two columns report the scaled difference between and the scaled sum of the intraday coefficient$\times 24/6.5$ and the overnight coefficient$\times 24/17.5$. The last two rows report the difference between the estimated coefficients on the *Common* and the *News* components. Independent variables are winsorized at 1% and 99% each month and standardized to have zero mean and unit variance. The sample period is from July 1993 to December 2021. The t-statistics with Newey and West (1987) adjusted standard errors are shown in parentheses.

	Close-to-Close	Intraday	Overnight	Intraday−Overnight (scaled)	Intraday+Overnight (scaled)
	(1)	(2)	(3)	(4)	(5)
CF Day *Common*	0.593	0.505	0.055	1.790	1.941
	(5.17)	(4.92)	(1.55)	(4.70)	(4.99)
CF Day *News*	0.624	0.508	0.085	1.759	1.993
	(5.57)	(5.22)	(2.97)	(5.03)	(5.42)
CF Night *Common*	0.044	-0.380	0.481	-2.063	-0.745
	(0.37)	(-4.26)	(8.78)	(-6.62)	(-2.13)
CF Night *News*	0.045	-0.222	0.308	-1.241	-0.397
	(0.53)	(-2.94)	(8.21)	(-4.41)	(-1.43)
Ret Day	√	√	√		
Ret Night	√	√	√		
Controls	√	√	√		
Intercept	1.048	0.723	0.775		
	(3.26)	(2.80)	(3.46)		
Avg. R^2(%)	6.789	7.807	6.177		
Avg. # Obs	2267	2267	2267		
CF Day:	-0.031	-0.003	-0.030		
Common−News	(-0.50)	(-0.05)	(-1.25)		
CF Night:	-0.001	-0.158	0.173		
Common−News	(-0.02)	(-3.11)	(4.46)		

TABLE A13

Intensity of cross-firm tug-of-war and future returns

This table presents returns of portfolios formed by abnormal cross-firm negative daytime reversals. Each month, stocks are sorted into deciles based on the abnormal frequency of cross-firm negative daytime reversals, AB_NR^C. Portfolios are equal weighted in Panel A and value weighted in Panel B. In addition to raw returns, I also calculate portfolio alphas using the Carhart model (Carhart, 1997) and the six-factor model of Fama and French (2015). Following Akbas et al. (2021), I exclude financial and utility firms and require a share price of at least one dollar before portfolio formations; for value-weighted portfolios, stocks in the largest 1% are omitted. The sample period is from May 1993 to December 2021. The t-statistics with Newey and West (1987) adjusted standard errors are shown in parentheses.

Panel A. Equal-weighted											
	Low	2	3	4	5	6	7	8	9	High	High-Low
Raw return	0.416	0.577	0.551	0.552	0.718	0.711	0.798	0.827	0.967	1.243	0.827
	(1.15)	(1.60)	(1.52)	(1.48)	(1.84)	(1.89)	(2.15)	(2.26)	(2.68)	(3.26)	(5.47)
Carhart alpha	-0.334	-0.245	-0.275	-0.308	-0.130	-0.170	-0.066	-0.049	0.083	0.328	0.661
	(-2.96)	(-2.44)	(-3.04)	(-4.11)	(-1.56)	(-2.10)	(-0.70)	(-0.52)	(0.70)	(2.33)	(4.49)
FF6 alpha	-0.377	-0.253	-0.201	-0.295	-0.076	-0.124	0.013	-0.029	0.088	0.261	0.638
	(-3.27)	(-2.67)	(-2.19)	(-4.02)	(-0.92)	(-1.68)	(0.12)	(-0.29)	(0.70)	(1.83)	(4.17)
Panel B. Value-weighted											
	Low	2	3	4	5	6	7	8	9	High	High-Low
Raw return	0.463	0.669	0.557	0.618	0.593	0.527	0.513	0.733	0.710	0.952	0.489
	(1.77)	(2.67)	(2.02)	(2.14)	(2.10)	(1.79)	(1.62)	(2.57)	(2.41)	(3.18)	(2.63)
Carhart alpha	-0.245	-0.112	-0.207	-0.209	-0.195	-0.305	-0.305	-0.060	-0.141	0.098	0.344
	(-1.86)	(-1.07)	(-2.28)	(-2.16)	(-2.78)	(-3.72)	(-2.92)	(-0.81)	(-1.47)	(0.81)	(1.95)
FF6 alpha	-0.361	-0.196	-0.192	-0.219	-0.176	-0.324	-0.253	-0.119	-0.199	-0.032	0.328
	(-2.98)	(-1.85)	(-1.92)	(-2.26)	(-2.45)	(-3.61)	(-2.62)	(-1.43)	(-1.92)	(-0.22)	(1.63)