# Cross-Insider Trading*

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**Abstract**

In this paper, we argue that insiders could access and even exchange nonpublic material information through professional networks and conduct cross-stock trading to exploit it, which we term " *cross-insider trading*". We use two novel datasets—a proprietary administrative transaction-level data from India and LinkedIn profiles–and provide strong evidence consistent with this argument. Specifically, we find that insiders trade more frequently on stocks where their former colleagues currently work, and such trading is not due to industry/local familiarity. We also find that these *cross-insider trading* can significantly predict future stock returns without reversal, whereas the trades of the same group of insiders have no such predictability on stocks in the same industry. More importantly, we use exogenous "moving-out" of linked insiders as quasi-exogenous shocks to address causality issues. *Cross-insider trading* constitutes a distinct form of insider trading and challenges the current regulatory framework.

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Insider trading, in which corporate insiders exploit confidential information for personal gain, undermines market fairness and efficiency and thus attracts large attention from regulators and academia. A large body of research has explored insiders' trading in their own firms (e.g, Lakonishok and Lee, 2001; Cohen, Malloy, and Pomorski, 2012; Ali and Hirshleifer, 2017; Alldredge and Cicero, 2015; Akbas, Jiang, and Koch, 2020; Hvide and Nielsen, 2024); however, little attention has been paid to their trades in other firms. This gap is particularly critical given that current regulations only require insiders to disclose trades in their own companies, leaving a large void in the oversight of trades involving other firms.[1] In this paper, we argue that insiders could access and even exchange material nonpublic information through professional networks and conduct cross-stock trading to exploit this information, which we term "*cross-insider trading*". Such *cross-insider trading* constitutes a distinct form of insider trading and can help insiders circumvent regulations, thereby challenging market fairness and efficiency.[2]

There are two empirical challenges in testing our argument. First, since regulations do not require insiders to disclose trades in other firms, we lack comprehensive insider cross-firm trading data. Second, we lack data on insiders' professional networks. We leverage two novel datasets to address these two challenges. The first comprises comprehensive administrative records from India's National Stock Exchange (NSE) during the period from January 2007 to June 2020, which allows us to observe insiders' complete transaction records. The second contains detailed pro-

[1]Recent studies provide suggestive evidence that insiders circumvent insider trading regulations by trading economically linked firms (Mehta, Reeb, and Zhao, 2021) or peer firms (Deuskar, Khatri, and Sunder, 2025).

[2]The *Raj Rajaratnam/Galleon Group, Anil Kumar, and Rajat Gupta insider trading cases* are one of the most well-known examples of insider trading through professional networks and support our argument. The case involves a vast network across technology and finance firms such as Intel, Google, and Hilton. Within these networks, corporate executives exploited their professional relationships to exchange private information and evade direct trading restrictions. For instance, Rajat Gupta, while serving on the boards of Goldman Sachs and Procter & Gamble, shared sensitive boardroom information with Rajaratnam, who then traded on this privileged intelligence to generate substantial illicit profits. This illustrates how cross-insider trading can be enabled by informal professional ties, which pose significant challenges for traditional regulatory compliance.

fessional background information from LinkedIn, which enables us to identify the professional network among insiders.

Using NSE transaction-level data and LinkedIn data, we test our central argument: insiders can access and even exchange material nonpublic information through professional networks and exploit it via cross-stock trading. This argument yields two testable predictions. First, insiders are more likely to trade stocks of firms connected through their networks. Second, these "*cross-insider trading*" contain information and can predict future returns. We conduct the following empirical analysis to test these two predictions.

We start by examining how professional networks affect insiders' trading. Specifically, we first define a pair of insiders as *linked insiders* if they had overlapping work experience at the same firm in the past, as documented on LinkedIn. Then we construct an insider-stock-month sample as follows. First, for each insider, the sample includes the stocks of firms where at least one linked insider currently works, as well as other stocks in the same industry as these firms. Note that including stocks in the same industry helps isolate the effect of the professional networks from other confounding factors (e.g., industry familiarity, Ben-David, Birru, and Rossi, 2019; Deuskar et al., 2025). To rule out the possibility that insiders have their own inside information about the stocks, we exclude firms from our sample for which focal insiders worked during our entire sample period.

The analysis of this sample provides strong evidence for our first prediction. That is, insiders are more likely to trade stocks of firms where their linked insiders currently work. The effect is highly statistically significant even after controlling for insider and industry fixed effects. The magnitude of the effect is also economically important. For example, having a linked insider increases the likelihood of trading by 67 bps, compared with the sample mean of just 24 bps.[3]

We further corroborate our evidence by zooming on earnings announcements. We find that insiders are not only more likely to trade stocks with linked insiders before earnings announcements, but they also trade in the same direction as the upcoming earnings news. This result provides compelling evidence that *cross-insider trading* does indeed have information motives.

We turn to examine whether *cross-insider trading* contains information (the second prediction of our argument). To this end, we aggregate *cross-insider trading* at the stock level. Specifically, for each stock $j$ in week $t$, we calculate the net buy dollar amount (the net buy share amount) of all *cross-insider trading* of this particular stock and scale it by the total trading dollar amount (the total trading share amount) of all insider trades. We term these scaled *cross-insider trading* as *cross-insider order flows*. We find that *cross-insider order flows* can significantly predict stock returns next week. In contrast, insiders' trading on other stocks in the same industry does not exhibit any return predictability. This sharp contract highlights that the return predictability of *cross-insider trading* does not arise from the industry expertise. [4]

We further conduct additional analyses to strengthen the argument. First, we examine the long-run return predictability of *cross-insider order flows* and find that the return predictability lasts for eight weeks without reversals, suggesting that the return predictability of *cross-insider order flows* is not driven by price pressure and is consistent with the information motive. Second, we exclude firms from the insider's own industry or firms located in the same city as the insider's firm and find that results barely change, suggesting that the return predictability of *cross-insider order*

[3]We find similar results when we consider the fraction of trading amount as the dependent variable.

[4]We also follow Seasholes and Zhu (2010) and Ben-David et al. (2019) to calculate holding-based calendar returns for *cross-insider trading* and other trading. We find that *cross-insider trading* significantly outperforms insiders' trades on other stocks in the same industry by about 4 bps per day in terms of risk-adjusted returns (e.g., controlling for Carhart four factors).

*flows* is not driven by industry information (e.g., Ben-David et al., 2019; Deuskar et al., 2025) and local information (e.g., Coval and Moskowitz, 1999; Ivković and Weisbenner, 2005; Massa and Simonov, 2006).

We further argue that information sharing on professional networks is likely to be bilateral. That is, if insiders indeed exchange information within their networks, when linked insiders profit from the focal insider's information and the subsequent trading of the focal insider's own stock, they are more willing to share their own information with the focal insider as payback. As a result, we expect that when a linked insider has profited from trading the focal insider's own firm, the focal insider is more likely to trade stocks with this linked insider, and such *cross-insider trading* contains more information. We indeed find strong supporting evidence for this argument in the data. Specifically, after a linked insider earns positive profits, the focal insider's likelihood of trading in her firm more than doubles (from 57 bps to 134 bps). Meanwhile, the return predictability of these *cross-insider trading* is 3.8 times greater than that of other *cross-insider trading*.

Thus far, we have provided strong evidence consistent with the argument that insiders can access and even exchange material nonpublic information through professional networks and exploit it through cross-stock trading. However, we are well aware that some unobservable factors might drive our results. To provide causal evidence that the return predictability of *cross-insider trading* originates from information sharing, we utilize plausible exogenous shocks–the "moving-out" of linked insiders from their firms–and conduct a difference-in-difference (*diff-in-diff*) analysis. These events are ideal for our identification, as the linked insiders' "moving-out" disrupts the professional connections between the focal insiders and the corresponding firms. To control for unobservable factors (e.g., industry familiarity), we use firms in the same industry as the affected firms as the control group. We argue that if the return predictability of *cross-insider trading* arises mainly from information sharing, we expect *cross-insider trading* to have strong return predictabilities before these "moving-out" events, but such predictabilities diminish or disappear afterward. We find that this is indeed the case in the data. We also confirm that the reduction in return predictability does not stem from pre-event trends. Overall, the evidence from the *diff-in-diff* analysis supports the argument that the return predictability of *cross-insider trading* originates from insiders' professional networks.

Overall, our study employs two novel datasets—NSE transaction records and LinkedIn profiles—to uncover a distinct form of insider trading, which we term *cross-insider trading*. This previously undocumented insider trading practice is a significant regulatory gap and poses a big challenge to market fairness and efficiency.

# 1 Liteature

Our paper contributes to the vast literature on insider trading. Early work focuses mainly on examining whether insider trading has information content (Lakonishok and Lee, 2001; Ravina and Sapienza, 2010; Jagolinzer, Larcker, Ormazabal, and Taylor, 2020; Eckbo and Smith, 1998; Jenter, 2005; Eckbo and Ødegaard, 2020; Hvide and Nielsen, 2024) and how insiders trade around major corporate events such as earnings announcements and M&As (Keown and Pinkerton, 1981; Cohen et al., 2012; Griffin, Shu, and Topaloglu, 2012; Augustin, Brenner, and Subrahmanyam, 2019). In response to regulatory constraints and declining profitability from trading in their own firms (Seyhun, 1992; Fishman and Hagerty, 1992; Bhattacharya and Daouk, 2002; Fernandes and

Ferreira, 2009; Jagolinzer, Larcker, and Taylor, 2011; Ali and Hirshleifer, 2017; White, 2020), a growing strand of literature documents that insiders also trade profitably in other companies' stocks (e.g., Tookes, 2008; Chen and Jorgensen, 2022; Ben-David et al., 2019; Deuskar et al., 2025; Mehta et al., 2021).

Among these studies, the work most related to us is Ben-David et al. (2019), Deuskar et al. (2025), and Mehta et al. (2021). Specifically, Ben-David et al. (2019) merges the brokerage account data of the Barber and Odean (2000) and insider trading files and finds that insiders are more likely to trade stocks in the same industry as their own firms and also make profits from these trades. They attribute the profitability of these trades to industry familiarity or fungible industry knowledge. Deuskar et al. (2025) uses a proprietary data set of all trades on the BSE (formerly the Bombay Stock Exchange) and finds that insiders utilize their private information about their own firms and trade peer stocks (e.g., stocks in the same industry) to circumvent insider trading regulations. In a similar spirit of Deuskar et al. (2025), Mehta et al. (2021) provides suggestive evidence that insiders trade in connected firms using information derived from their own firms. While we also focus on insiders' trading on firms beyond their own firms, the type of insider trading is conceptually different from prior studies. Particularly, we identify a distinct channel–professional network among insiders–through which insiders obtain and profit from the information about other firms. This type of insider trading can help insiders circumvent regulatory scrutiny and poses a big challenge to market fairness and efficiency.

Our study also contributes to the literature on communication in financial markets, focusing on the role of social networks in information transmission (Shiller, 2017; Hirshleifer, 2020). Prior studies have identified several channels of information sharing, including educational networks that link market participants via shared educational experiences (Cohen, Frazzini, and Malloy, 2008, 2010), geographic neighboring with which neighbors or colleagues could share information (Ivković and Weisbenner, 2007; Hvide and Östberg, 2015; Huang, Hwang, and Lou, 2021a; Hirshleifer, Peng, and Wang, 2025), and the role of financial intermediaries such as brokers in disseminating information about large trades or upcoming analyst reports (Irvine, Lipson, and Puckett, 2007; Barbon, Di Maggio, Franzoni, and Landier, 2019; Di Maggio, Franzoni, Kermani, and Sommavilla, 2019). This body of work demonstrates that such communication can confer significant informational advantages—though these are occasionally tempered by regulatory measures. Additional evidence indicates that information leakage also manifests in insider trading, where brokers enable affiliates to benefit from nonpublic information (Li, Mukherjee, and Sen, 2021).

We extend the literature on communication by exploring a previously underexplored channel: information sharing among corporate insiders. In contrast to the prevalent focus on information flowing from insiders to outsiders, we uncover that professional ties among insiders themselves form a potent conduit for material nonpublic information. Thus, our study contributes twofold. First, it identifies insider networks as a distinct mechanism of information transmission. Second, by focusing on sharing within insider networs, it offers new insights into how these networks can undermine standard regulatory efforts against insider trading.

The remainder of the paper is organized as follows. Section 2 describes data and empirical methodologies, Section 3 presents main empirical results, Section 4 presents additional analysis and the identification strategy, and Section 5 concludes.

# 2 Data and Sample Construction

In this section, we provide detailed descriptions of our data and discuss how we construct our sample. Section 2.1 describes the data, Section 2.2 describes how we identify insiders by merging the National Stock Exchange of India (NSE) and the insider trading filings from the India-Infobase and extract insider professional background inforamtion from LinkedIn, and Section 2.3 describes how we construct professional networks of insiders and how we define *cross-insider trading*.

## 2.1 Data Description

This subsection describes the data used in our study. Our data includes comprehensive administrative transaction data from the National Stock Exchange of India (NSE), Indian insider trading filings from NSE-Inforbase, and LinkedIn. In what follows, we provide more detailed descriptions of each data set.

The first data set we use is a proprietary administrative transaction dataset from the National Stock Exchange of India (NSE), covering the period from January 2004 to June 2020. Compared to the data sets used in prior literature, our data has at least two advantages. First, our data set is comprehensive, as the NSE is the leading exchange in India, based in Mumbai, and the fifth-largest stock exchange in the world by total market capitalization, exceeding $5 trillion in May 2024. Second, in this transaction-level data set, we can observe the investor ID–the anonymized Permanent Account Number (PAN), the transaction date, the security ticker, the number of shares bought or sold, and the execution prices. The granularity and completeness of our data enable us to observe insiders' complete trading records and systematically analyze how insiders trade in other firms in addition to their own firms. To ensure data consistency, we only include transactions associated with stocks listed in the Prowess Database maintained by the Centre for Monitoring Indian Economy (CMIE). We also exclude ETFs/foreign stocks and focus on domestic stocks in our analysis.

The second dataset used in our study is the insider trading filings from NSE-Infobase, India's first and only database that provides details and analysis of insider trades at both the shareholder and company level. Under Indian insider trading regulations, directors, officers, and significant shareholders (holding more than 5% of voting rights) in a listed Indian company must disclose any changes in their shareholdings to the relevant stock exchange(s). The disclosed information from the insider trading filings includes the transaction date, insider's name, stock identifier, acquisition or sale method, and the number of shares involved. These filings may also cover transactions that are not executed on an exchange, such as share allotments under employee stock ownership plans, off-market transactions, and the exercise of employee stock options. For our analysis, we only consider insider-reported trades executed on the secondary market. Matching NSE transaction data with insider trading filings can identify insiders and track their trading (see details in Section 2.2).

To identify the professional networks of insiders, we use the self-reported LinkedIn profiles, which typically include details about individuals' past employers and tenure periods. For the majority of profiles, these employment histories are clearly defined. We discard entries with ambiguous or incomplete descriptions to ensure the reliability of the professional network construction. These refined data are crucial for constructing accurate employment histories and establishing professional connections among insiders, which form the basis of our professional network.

Finally, we complement our regulatory data with publicly available data. First, we obtain the information on stock prices, market capitalization, book-to-market ratios, and adjustment factors from the Prowess Database, maintained by the Centre for Monitoring Indian Economy (CMIE). Second, we obtain the data on earnings announcements and industry classifications from Refinitiv.

## 2.2 Identifying Insiders and Sample Construction

This subsection describes how we identify insiders from the NSE data and extract their professional background information from LinkedIn.

As the NSE data only provides the anonymized Permanent Account Number (PAN) of traders, we first need to identify insiders. To this end, we start with the insider trading filings from the NSE-Infobase and match them with the NSE transaction-level data. Given that each reported insider trade in the NSE-Infobase can potentially match with multiple trades in the NSE data, we adopt a strict matching approach by exploiting non-round-lot trades, which are more likely to have unique matches. Specifically, we focus on insiders who have reported at least two trades, with at least one being an odd-lot. We then take the following two steps. In the first step, we match corporate insiders to trade accounts using only odd-lot transactions, retaining only those with a unique match. To ensure accuracy, we further require that the uniquely matched account must have at least one additional trade with a perfect date and quantity match, and we retain only pairs with a unique trade match. Note that this two-step process guarantees that an insider is uniquely matched to an account in the NSE data at least twice, with at least one of those matches being an odd-lot transaction. In total, we identify 10,362 insiders in the NSE data.

We notice that the insider trading filings from India-Inforbase also report the trading of non-human entities (e.g., corporations). Thus, we exclude insiders that are shown as non-human entities in India-Inforbase and discard insiders who execute more than 1,500 trades in a single month (unlikely to be managed personally by the insider) to ensure data quality. We also follow Ben-David et al. (2019) and exclude small trades below 10000 Rupees (approximately 113 USD) to reduce noise.

To identify the professional network, we manually collect LinkedIn profiles for matched insiders. A big challenge in collecting LinkedIn profiles of insiders is the prevalence of common names in India. To tackle this challenge, we employ a three-step verification rule: 1) *Name Matching*: the LinkedIn profile name must correspond to the insider under common Indian naming conventions; 2) *Company Matching*: the insider's work history must include the specific firm with which they are associated as an insider; 3) *Position Matching*: the individual must have held a managerial or officer-level role at the corresponding company.

We use insider-reported trades from India-Inforbase regulatory filings to more precisely extract the employment history of insiders in their companies. That is, for each insider-firm pair, we define the employment history as the period from 6 months before the first reported trade to 6 months after the last reported trade. This approach yields an average employment history of 1,518 days (approximately 4 years) for identified insiders.

The above process yields a final sample of 5,640 corporate insiders with identified LinkedIn profiles, accounting for 4,520,424 trades during the sample period from January 2007 to June 2020.

## 2.3 Identifying Linked Insiders and Cross-Insider Trading

This subsection presents the core of our empirical design: defining linked insiders through professional networks and then identifying the trades most likely motivated by this channel, which we term "*cross-insider trading*."

To study the impact of professional networks on insiders' cross-stock trading, we first define a pair of insiders as *linked insiders* as follows. Specifically, insiders $A$ and $B$ are considered linked if their professional trajectories, as documented on LinkedIn, indicate that they worked for the same company with an overlap period of more than one year. For such a pair $(A,B)$, we define the **meet time** ($t_m$) as the point in time exactly 12 months after the start date of their overlapping employment. This 12-month requirement is not arbitrary and ensures a sufficient period of professional acquaintance to establish a trust-based information channel. Note that the results are robust for alternative requirements. Lastly, for a fair comparison, we require that the sample for each insider-stock pair have the same windows before and after the event.

After identifying linked insiders, we then define a *cross-insider trading* as follows. Consider insider $A$ of firm $X$ during her tenure $[t_1^A, t_2^A]$ in firm $X$. A transaction in which the insider $A$ trades the stock of another firm $Y$ in month $t$ is classified as *cross-insider trading* if the following conditions are met:

1. There exists an insider $B$ of firm $Y$ during here tenure $[t_1^B, t_2^B]$, and $B$ is a linked insider of $A$.
2. The transaction month $t$ occurs after the *meet time* $t_m$ of the pair $(A,B)$ and within the overlapping period of their employment periods, i.e., $t > t_m$ and $t \in [t_1^B, t_2^B]$.
3. To ensure that the trade is motivated by the professional network rather than the insider $A$'s

own information, we require that $A$ never works for firm $Y$ at any point in our entire sample period.

In short, we define insider $A$'s *cross-insider trading* of stock $Y$ as the one that occurs during a period when the insider $B$, because he is a valid insider of firm $Y$, can access material nonpublic information about firm $Y$, and after a sufficient professional acquaintance. It is clear that our definition of *cross-insider trading* is well-suited for studying how professional networks affect insiders' trading behaviors.

We are aware of the possibility that the insider $A$ trades stock $Y$ of the insider $B$ because she is familiar with the industry of firm $Y$ and thus possess industry-wide information (Ben-David et al., 2019; Deuskar et al., 2025) of stock $Y$. This is plausible, since insiders $A$ and $B$ used to work together at the same firm, suggesting that insider $A$ likely worked in the industry of the firm $Y$. To isolate the effect of the professional network, we consider insiders' (e.g., the insider $A$) trading in other stocks in the same industry as the stocks (e.g., stock $Y$) in their *cross-insider trading* . To be specific, we classify a trade by the insider $A$ as as *other trading* if it is executed on a firm $Z$ in the same industry of a firm that is part of any *cross-stock trading* of the insider $A$, given that two conditions are met: first, at the time of the trade $t$, the insider $A$ has no linked insiders at firm $Z$; and second, the insider $A$ must never have served as an insider of firm $Z$ at any point in our entire sample period. This second condition is critical, as it ensures that the trade is not motivated by insider $A$'s own information or expertise about firm $Z$.[5]

[5]We further conduct two additional tests to rule out possibilities of industry information (e.g., Ben-David et al., 2019; Deuskar et al., 2025) and local information (e.g., Coval and Moskowitz, 1999; Ivković and Weisbenner, 2005; Seasholes and Zhu, 2010; Massa and Simonov, 2006), That is, we exclude trades involving firms in the same industries as the insiders currently work for or used to work for or involving firms resident in the same cities where the insiders currently work; We find that the results are unchanged.

Our ultimate goal is to study whether *cross-insider trading* is information-driven. Thus, after identifying *cross-insider trading* and *other trading*, we aggregate them at the stock level. Specifically, for each stock $j$ in week $t$, we calculate the net buy dollar amount (the net buy share amount) of all *cross-insider trading* of this particular stock and scale it by the total trading dollar amount (the total trading share amount) of all insider trades. We term these scaled *cross-insider trading* as *cross-insider order flows*. Similarly, we aggregate *other trading* into *other order flows*.

# 3 Main Empirical Results

In this section, we describe our main results. Section 3.1 tests whether insiders are more likely to trade on firms with linked insiders (our first hypothesis). Section 3.2 examines the return predictability and information (our second hypothesis).

## 3.1 Professional Networks and Insider' Trading Across Stocks

As our first hypothesis states, if insiders obtain information through professional networks, we should observe them trading more frequently in connected firms—specifically, those with former colleagues acting as current insiders.

To formally test this prediction, we first construct a sample at the level of insider-stock-month. For an insider each month, our sample includes two types of candidate stocks. The first type consists of firms where at least one of the focal insider's former colleagues currently holds an insider position, which we term "*cross-linked stocks*". The second type includes peer firms that operate in the same industry as these linked firms but have no such linked insiders, which we term "*other stocks*". Note that *other stocks* serve as a control group to account for insiders' familiarity, as documented in prior studies (e.g., Ben-David et al., 2019). We further exclude firms for which the focal insider worked at any point in our entire sample period to rule out the possibility that insiders possess their own information rather than information from professional networks.

Based on the insider-stock-month sampple, we conduct the following regression analysis:

$$\mathbf{I}_{trade,i,j,t} = \alpha + \beta\, \mathbf{I}_{linked,i,j,t} + \gamma Controls + FE + \varepsilon_{i,j,t}, \tag{1}$$

where the dependent variable, $\mathbf{I}_{trade,i,j,t}$ is a dummy equal to one if insider $i$ trades firm $j$ during month $t$, and zero otherwise. For the interpretation of the coefficient, we multiply the dependent variable by 100. The key explanatory variable, $\mathbf{I}_{linked,i,j,t}$, is a dummy variable equal to one if in month $t$ there is at least one former colleague of insider $i$ working for firm $j$, and zero otherwise. We include firm-level characteristics as control variables —firm size, book-to-market, momentum, and past returns. We also consider insider and industry fixed effects. Standard errors are clustered at the insider, firm, and time levels.

Table 2 reports the results. As we can see, the coefficients on $\mathbf{I}_{linked,i,j,t}$ are positive and highly significant across all specifications, strongly supporting our first hypothesis. For exampple, after controlling for a full set of controls and fixed effects, the coefficient is 0.675 (*t-statistic* = 4.631). It suggests that the presence of linked insiders increases the likelihood of trading by 67 bps, an economically significant effect given the sample mean of 24 bps. Such an effect can also be visualized in Figure 1, where we compare insiders' actual trading likelihood in "*cross-linked stocks*" and a benchmark of a hypothetical random trading likelihood in these stocks.[6]

[6]For robustness, we repeat the regression in Equation 1 but consider the fraction of trading dollar amount as the

We further corroborate our evidence by zooming on earnings announcements. As key information events, earnings announcements have a clear timing and information content, allowing us to better identify informed trading (e.g., Huang, O'Hara, and Zhong, 2021b). We use the same regression specifications in Equation 1, but focus only on insider trades in the 10 to 2 trading days before an earnings announcement. As reported in Panel A of Table 3 reports, we find that insiders are more likely to trade on "*Cross-linked stocks*" before earnings annoucments, consistent with the results in Table 2.

We turn to examine whether insiders trade correctly before the earnings announcements. To this end, we first measure the information content of the earnings announcements using the cumulative abnormal return adjusted for DGTW (Daniel, Grinblatt, Titman, and Wermers, 1997) around the announcement dates and perform the following regression:

$$\mathbf{I}_{net\ buy,i,j,t} = \alpha + \beta_1 \mathbf{I}_{linked,i,j,t} + \beta_2 CAR_{3,j,t} + \beta_3 CAR_{3,j,t} \times \mathbf{I}_{linked,i,j,t} + \gamma Controls + FE + \varepsilon_{i,j,t}, \tag{2}$$

where dependent variable $\mathbf{I}_{net\ buy,i,j,t}$ is an indicator that equals one if insider $i$ is a net buyer of stock $j$ in the 10 to 2 trading days before the earnings announcement in quarter $t$, and zero otherwise. The key independent variable, $\mathbf{I}_{linked,i,j,t}$, is defined as before. $CAR_{3,j,t}$ is the 3-day DGTW-adjusted cumulative abnormal return around the earnings announcements.

Panel B of Table 3 reports the results. The coefficient estimate, $\beta_3$, is significantly positive in all specifications, suggesting that insiders indeed trade in the same direction as the upcoming news on linked firms. This result provides compelling evidence that *cross-insider trading* does indeed

dependent variable. As shown in Appendix Table A.1 and Appendix Figure A.1, the results are robust.

have information motives.

In sum, this section uncovers *cross-insider trading*–insiders are more likely to trade in firms with linked insiders. It is worth noting that such *cross-insider trading* is not driven by industry familiarity or expertise, as we use stocks in the same industry as the linked firms for comparison.

## 3.2 Cross-Insider Trading Performance

Having established the fact that insiders are more likely to trade on connected firms, we turn to examine the return predictability of these trades. To this end, we aggregate *cross-insider trading* at the stock level. Specifically, for each stock j in week t, we calculate the net buy dollar amount (the net buy share amount) of all cross-insider trading of this particular stock and scale it by the total trading dollar amount (the total trading share amount) of all insider trades. We term these scaled *cross-insider trading* as *cross-insider order flows*. Similarly, we aggregate *other trading* into *other order flows*. We then follow (Greenwood and Hanson, 2012) and conduct the following panel regression to examine the return predictability of order flows:

$$Return_{j,w+1} = \alpha + \beta\, Order\,flow_{j,w} + \gamma Controls + FE + \varepsilon_{j,w} \tag{3}$$

where the dependent variable is the stock return of stock $j$ at week $w+1$. The key independent variable is $Order\,flow_{j,w}$, which could be *cross-insider order flows* or *other order flows* at stock $j$ at week $w$. We also control for firm-level characteristics, including firm size, book-to-market, momentum, and past returns. We also include time-fixed effects to examine the cross-sectional predictability of order flows (see the argument in Greenwood and Hanson, 2012). To ensure sufficient cross-sectional variation, we keep only weeks with at least 15 observations. Standard errors are clustered at the time and firm levels.

Table 4 reports the results. As shown in Columns (1) and (2), both the dollar-amount-based and share-amount-based *cross-insider order flows* exhibit a statistically significant positive return predictability. In contrast, the return-predictability of *other order flows* is insignificant. This stark contrast underscores that *cross-insider order flows* contains information, and this information does not arise from industry-level expertise.

We conduct a series of robust checks. First, we confirm that the results are robust using Fama-MacBeth regressions (Fama and MacBeth, 1973) (see Appendix Table A.2). Second, we show that the results are robust to sample filters about the minimum number of valid observations per week (see Appendix Table A.3). Third, we follow Seasholes and Zhu (2010) and Ben-David et al. (2019) and consider holding-based calendar returns for insiders' trading on *cross-linked firms* and *other firms* (the peer firms in the same industry as the linked firms). As shown in the Appendix Table A.4, *cross-insider trading* significantly outperforms *other trading*, after adjusting for common risk factors (Fama and French, 1996; Daniel et al., 1997; Carhart, 1997).[7]

Some may be concerned that the return predictability of *cross-insider trading* arises from the temporary price pressure. This is very unlikely as insiders' trades account for a small proportion of trading in the market. Nevertheless, we conduct formal exercises to address this concern. Specifically, we examine the long-run return predictability of *cross-insider trading*. Table 5 and Figure 2 show that the return predictability of *cross-insider trading* lasts for eight weeks without reversals, suggesting that *cross-insider trading* indeed contains information.

[7]In untabulated results, we conduct a transaction-based performance analysis and find similar results.

We also take advantage of firm heterogeneity and examine how the return predictability of *cross-insider trading* varies with firm sizes. Specifically, each week, we classify firms in the bottom size quartile into the group of small firms and classify the remaining firms into the group of large firms. After that, we repeat the exercise of Table 4 and report the results in Table 6. We find that the return predictability of *cross-insider order flows* is more pronounced among small firms, consistent with the notion that the market for small stocks is less efficient, and informed trading exhibits stronger return predictability (Bhushan, 1989; Hong, Lim, and Stein, 2000; Piotroski and Roulstone, 2004; Hou and Moskowitz, 2005).

In sum, Tables 4, 5, and 6 demonstrate that *cross-insider trading* can significantly forecast future returns without reversals. In contrast, these insiders' trading on peer stocks in the same industry as the linked firms has no such return predictability, highlighting that the return predictability of *cross-insider trading* does not arise from industry-level expertise.

# 4 Further Studies and the Identification Strategy

In this section, we conduct further studies to corroborate our evidence. Specifically, Section 4.1 further confirms that the return predicability of *cross-insider trading* does not arise from industry and local information, Section 4.2 shows the existence of bilateral information sharing, and Section 4.3 addresses the endogenous issues.

## 4.1 Robustness Checks: The Role of Industry and Local Information

Thus far, we have provided strong evidence that insiders are more likely to trade their linked firms' stocks, and that these trades contain information, consistent with our argument that insiders can access material nonpublic information through professional networks and exploit. However, some may be concerned that these findings are arising from insiders' industrial (Ben-David et al., 2019; Deuskar et al., 2025) or local (Coval and Moskowitz, 1999; Ivković and Weisbenner, 2005; Seasholes and Zhu, 2010) familiarity. In this section, we conduct a series of strict robustness tests to rule out these possibilities.

We first confirm that the high likelihood of insiders' trading on linked firms is not driven by the industry or local familiarity. Specifically, to rule out the possibility of industry familiarity, we exclude the insider-stock sample in which the stocks belong to the industries where the insiders used to work or currently work at any time during the sample period, and repeat the exercises of Table 2. To rule out the possibility of local familiarity, we exclude the insider-stock sample in which the firm's headquarters is in the same city where the insider currently works and repeat the exercises of Table 2. Panel A of Table 2 reports the results on the sample excluding stocks in insiders' industries, Panel B reports the results on the sample excluding stocks in insiders' cities. As we can see, the coefficients on *cross-linked* dummy $\mathbf{I}_{linked}$ are statistically significant and positive across all specifications, suggesting that insiders are more likely to trade on *cross-linked stocks* after controlling for industry or local familiarity.

We then turn to demonstrate that the return predictability of *cross-insider trading* is not driven by the industry or local familiarity. To this end, we focus on the samples in Table 2 (excluding stocks in insiders' industries or excluding stocks in insiders' cities) and reconstruct *cross-insider* *order flow* as Table 4. Table 8 reports the results and confirms that the return predicabilities of *cross-insider order flow* are robust after controlling for industry or local familiarity.

## 4.2 Reciprocal Cross-Insider Trading

In this section, we extend our study and argue that information sharing on professional networks tends to be bilateral. Specifically, if insiders do exchange information within their networks, then when a linked insider profits from the focal insider's information—and subsequently trades the focal insider's stock—they become more inclined to reciprocate by sharing their own information in return. As a result, we expect that after a linked insider has profited from trading the focal insider's firm stock, the focal insider becomes more likely to engage in stock trading with that linked insider. Moreover, such *cross-insider trading* is expected to contain more information. This bilateral information exchange and subsequent *cross-insider trading* are very plausible under current insider trading regulations, as they provide "hidden mechanisms" for insiders to circumvent legal constraints while still capitalizing on their insider information.

To examine whether bilateral information sharing exists, we formally define *reciprocal cross-insider trading* as a special case of *cross-insider trading*: an insider is trading on a *cross-linked* firm, but at least one linked insider of the firm has profited from trading on the focal insider's own firm since the focal insider has been an insider in the firm. To show whether textitReciprocal cross-insider trading exists, we perform the following regression similar to Table 2:

$$\mathbf{I}_{trade,i,j,t} = \alpha + \beta_1 \mathbf{I}_{linked,i,j,t} + \beta_2 \mathbf{I}_{linked,i,j,t} \times \mathbf{I}_{reciprocal,i,j,t} + \gamma Controls + FE + \varepsilon_{i,j,t}, \quad (4)$$

where $\mathbf{I}_{trade,i,j,t}$ and $\mathbf{I}_{linked,i,j,t}$ are defined as Equation 1. The key indepedent variable $\mathbf{I}_{bilateral,i,j,t}$ is a dummy variable equal to one if at least one insider of firm $j$ is the linked insider of insider $i$ and also has profited from insider $i$'s own firm (e.g., stock $i$) since insider $i$ is an insider of the firm, and zero otherwise. It is clear that the interaction term between $\mathbf{I}_{linked,i,j,t}$ and $\mathbf{I}_{bilateral,i,j,t}$ can capture the possibility of *reciprocal cross-insider trading*.

Table 9 reports the results. As we can see, the coefficients on the interaction term between $\mathbf{I}_{linked,i,j,t}$ and $\mathbf{I}_{bilateral,i,j,t}$ are highly statistically significant and positive, suggesting the existence of *reciprocal cross-insider trading*. The magnitude is notable. For example, in Column (4), the effect of *reciprocal cross-insider trading* increases the likelihood of a trade by 134 bps, which is more than double the effect of mere *cross-insider trading* (57 bps).[8]

We further examine the return predictability of *reciprocal cross-insider trading* following the same procedure of Tables 4 and 5. Table 10 reports the predicability of *reciprocal cross-insider trading* on the next week's stock return, and Figure 3 plots the long-run return predictabilities. It is evident that *bilateral cross-insider trading* exhibits strong return predictability, which is 3.8 times greater than that of mere *cross-insider trading*.

In summary, we find strong supporting evidence for the bilateral information exchange and *reciprocal cross-Insider trading*. The results in this section not only strengthen our argument but also uncover a significant regulatory gap. Given that current regulations only require insiders to disclose trades in their own companies, insiders do not necessarily trade on their own insider information; instead, they exchange it with other insiders to capitalize on it.

[8] We obtain similar results when we consider the fraction of trading dollar amount as the dependent variable (see Appendix Table A.5).

## 4.3 Identification: Cross-linked Insider Move Out

Thus far, the analysis in the above sections provides strong evidence consistent with the argument that insiders access—and potentially exchange—material nonpublic information through professional networks, which they exploit via *cross-insider trading*. That said, we acknowledge the potential influence of unobservable confounding factors. To establish the link between information sharing and the return predictability of *cross-insider trading*, we exploit plausible exogenous shocks arising from the "moving-out" of linked insiders from their firms and implement a difference-in-differences (diff-in-diff) design. These "moving-out" events are ideal for our identification, as they disrupt the professional ties between focal insiders and the relevant firms. To account for unobserved confounding factors, such as industry familiarity, we use firms in the same industry as the affected firms as the control group. We contend that if the return predictability of cross-insider trading stems primarily from information sharing, it should be pronounced prior to a linked insider's departure but weaken or disappear following the event.

In our insider-firm sample, we use "*moving out*" of linked insiders as quasi-exogenous shocks, where linked insiders have valid professional network connections to insiders in this sample. Specifically, we identify linked insiders' "*moving out*" events as follows. First, for each linked insider, we identify her "*moving out*" event from her employment history using the procedure in Section 2.2. To avoid ambiguous "move-out" timing, we keep events where insiders are connected to linked firms via only one linked insider. In fact, if insiders are connected to linked firms through multiple linked insiders, the linked insider's "move-out" is ineffective. Second, for each event in the first step, we focus on the window that includes the 3 years before and after the move-out month for the *diff-in-diff* analysis. Thus, we include only events that occur three years after our data become available and three years before the end of our sample. Third, to ensure sufficient samples for statistical tests, we require the linkage between the focal insider and the linked firm to be valid for at least 12 months before each event. Lastly, we impose the symmetry on the window lengths before and after the "*moving out*" for a fair comparison.

After identifying "*moving out*" events, we construct the sample for the *diff-in-diff* analysis as follows. For each "*moving out*" event, we consider insiders who have linked insiders of the affected firm as the treatment group and include all of their trades during the event window. We consider the stocks in the same industry as the affected firm in the control group, but only focus on trades of the same group of insiders in the treatment group. More importantly, we further require that the stocks in the control group have never been linked to any focal insider in the event. Note that considering this control group can effectively control for insider fixed effects and industry familiarity. After that, we conduct the following "*diff-in-diff*" analysis to examine the return predictability of each trade:

$$CAR_{20,j,t} = \alpha + \beta_1 \mathbf{I}_{linked,i,j,t} + \beta_2 Post_{j,t} + \beta_3 \mathbf{I}_{linked,i,j,t} \times Post_{j,t} + \gamma Controls + FE + \varepsilon_{j,t}, \tag{5}$$

where the dependent variable, $CAR_{20,j,t}$, is the signed 20-day-ahead DGTW-adjusted cumulative return of stock $j$ after insider $i$' trade at date $t$. Specifically, if the trade is a buy, $CAR_{20,j,t}$ is simply the 20-day-ahead DGTW-adjusted cumulative return of stock $j$ at date $t$; we multiply this cumulative return by -1 if the trade is a sell. The independent variable $\mathbf{I}_{linked,i,j,t}$ is defined as before. $Post_{j,t}$ is a dummy variable equal to one if date $t$ is after the "*moving out*" event, and zero otherwise. The coefficient of the interaction term, $\mathbf{I}_{linked,i,j,t} \times Post_{j,t}$ can show whether the return predictability of *cross-insider trading* becomes weaker or disappears after linked insiders "*moving* *out*".

Table 11 reports the results and has strong evidence that the return predictability of *cross-insider trading* disappears after linked insiders "*moving out*". For example, as shown in column (2), while the coefficient of $\mathbf{I}_{linked,i,j,t}$ is positive and statistically significant (0.877 with *t-statistics=2.025* ), the coefficient of the interaction term, $\mathbf{I}_{linked,i,j,t} \times Post_{j,t}$ is negative and statistically significant (-1.250 with *t-statistics=-2.184*). These results demonstrate that *cross-insider trading* is profitable when linked insiders work for the firm, but such return predictability disappears after they leave the firm. We further confirm that these results are not arising from the pre-event trends (see columns (3) and (4)).[9]

# 5 Conclusion

In summary, our study uses two novel datasets—a proprietary administrative trading data from NSE and LinkedIn profiles–to uncover a distinct form of insider trading, which we term cross-insider trading. Specifically, We provide strong and rich evidence that insiders indeed exploit material nonpublic information accessed through their professional networks by trading in each other's stocks. More importantly, we use the exogenous "moving-out" of linked insiders as quasi-exogenous shocks to information sharing and conduct a *diff-in-diff* analysis to provide causal evidence that the return predictability of *cross-insider* trading indeed originates from information sharing within the professional networks.

[9]We conduct robustness checks for our identification strategy. First, we consider alternative window lengths (e.g., 2 years before and after the event) and show that the results are robust (see Appendix Table A.6. Second, we relax the filter in the sample construction. Specifically, we keep events where insiders are connected to linked firms via multiple linked insiders and show the results are robust (see Appendix Table A.7).

Our study not only contributes to the literature on insider trading, particularly on insider trading in other stocks, but also uncovers a significant regulatory gap that challenges market fairness and efficiency. The prevailing frameworks require insiders to disclose trades in their own firm's stock, yet they fail to cover *cross-insider trading*, thereby creating a vast and unmonitored arena for potential exploitation.

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Table 1 **Summary Statistics.** This table presents summary statistics on our sample, covering the period from January 2007 to June 2020. *cross-insider order flows*$_{\$}$ (*cross-insider order flows*$_{share}$) are stock-week level aggregated net buy dollar amount (net buy share amount) of all *cross-insider trading*, scaled by total trading dollar amount (total trading share amount). Similarly, *other order flows*$_{\$}$ and *other order flows*$_{share}$ are scaled and aggregated order flows of *other trading*. Firm characteristics include *BM* (book-to-market ratio), $lnME$ (log of market capitalization), $MOM$ (momentum), and $Return_{m-1}$ (past 1-month return). For each variable, we report the number of observations, mean, standard deviation, and key percentiles.

| | No. Obs. | Mean | SD | 25th | 50th | 75th |
|---|---|---|---|---|---|---|
| *Cross-insider order flow*$_{\$}$ | 10544 | -0.053 | 0.507 | -0.207 | -0.006 | 0.076 |
| *Other order flow*$_{\$}$ | 54583 | 0.013 | 0.788 | -0.987 | 0.000 | 1.000 |
| *Cross-insider order flow*$_{share}$ | 10544 | -0.052 | 0.507 | -0.207 | -0.005 | 0.078 |
| *Other order flow*$_{share}$ | 54583 | 0.013 | 0.788 | -0.987 | 0.000 | 1.000 |
| *BM* | 55739 | 0.607 | 0.709 | 0.192 | 0.363 | 0.780 |
| $lnME$ | 58087 | 11.697 | 1.765 | 10.534 | 11.675 | 12.949 |
| $MOM$ | 56688 | 0.195 | 0.588 | -0.152 | 0.098 | 0.404 |
| $Return_{m-1}$ | 58129 | 0.015 | 0.137 | -0.056 | 0.007 | 0.077 |

Table 2 **Likelihood of *Cross-Insider Trading*.** This table examines whether insiders are more likely to trade *cross-linked* firms. For each insider, we include *cross-linked* firms and firms in the same industries as the linked firms in our sample but exclude firms where the focal insider works at any point in our sample period. The dependent variable is an trade dummy equal to one if insider trades on the firm in the month, and zero otherwise. For the interpretation of the coefficient, we multiply the dependent variable by 100. The key independent variable, $\mathbf{I}_{linked}$, is an indicator equal to one if the firm is *cross-linked* to the insider, and zero otherwise. Other control variables include firm size, book-to-market ratio, momentum, and past 1-month return. T-statistics, based on standard errors clustered at insider, firm, and time levels, are reported in parentheses. The sample period is from January 2007 to June 2020. Statistical significance: $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

| | (1)<br>$\mathbf{I}_{trade,m}$ | (2)<br>$\mathbf{I}_{trade,m}$ | (3)<br>$\mathbf{I}_{trade,m}$ | (4)<br>$\mathbf{I}_{trade,m}$ |
|---|---|---|---|---|
| $\mathbf{I}_{linked,m}$ | 1.003*** | 0.679*** | 0.674*** | 0.675*** |
| | (5.581) | (4.466) | (4.520) | (4.631) |
| $lnME_{m-1}$ | | 0.114*** | 0.109*** | 0.105*** |
| | | (7.784) | (7.751) | (7.798) |
| $BM_{m-1}$ | | 0.019*** | 0.018*** | 0.015*** |
| | | (4.260) | (4.310) | (4.337) |
| $MOM_{m-1}$ | | -0.023*** | -0.022*** | -0.019** |
| | | (-2.852) | (-2.765) | (-2.564) |
| $Return_{m-1}$ | | -0.059* | -0.055* | -0.051* |
| | | (-1.905) | (-1.780) | (-1.662) |
| Insider FE | No | No | Yes | Yes |
| Industry FE | No | No | No | Yes |
| # Obs. | 50,463,879 | 44,867,769 | 44,867,769 | 44,867,769 |
| Adj. $R^2$ | 0.002 | 0.004 | 0.025 | 0.025 |

Table 3 ***Cross-Insider Trading* and Earnings Announcements.** This table investigates *cross-insider trading* before earnings announcements. Panel A examines if insiders are more likely to trade *cross-linked* firms. Sample includes both *cross-linked* firms and *other* firms and exclude insiders' own firms. The dependent variable is an indicator equal to one if the insider trades the stock between 10 to 2 trading days before the announcement. For interpretability, we multiply the dependent variable by 100. The independent variable, $\mathbf{I}_{linked}$, is an indicator equal to one if the firm is *cross-linked* to the insider, and zero otherwise. Panel B tests if *cross-insider trading* is in the same direction as the earnings news. The dependent variable is an indicator equal to one if the insider is a net buyer from 10 to 2 trading days before the announcement, and zero otherwise, we also multiply the dependent variable by 100 for coefficient . $CAR_3$ is the DGTW-adjusted cumulative abnormal return from one trading day before to the one trade day after the announcement date . T-values are in parentheses, based on standard errors clustered at insider, firm, and time levels. Other control variables include firm size, book-to-market ratio, momentum, and past 1-month return. The sample period is from January 2007 to June 2020. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

**Panel A: Likelihood of *Cross-Insider Trading***

| | (1) $\mathbf{I}_{trade,m}$ | (2) $\mathbf{I}_{trade,m}$ | (3) $\mathbf{I}_{trade,m}$ | (4) $\mathbf{I}_{trade,m}$ |
|---|---|---|---|---|
| $\mathbf{I}_{linked,m}$ | 0.510*** | 0.344*** | 0.341*** | 0.341*** |
| | (5.290) | (4.203) | (4.292) | (4.384) |
| $lnME_{m-1}$ | | 0.065*** | 0.062*** | 0.059*** |
| | | (7.007) | (6.919) | (6.941) |
| $BM_{m-1}$ | | 0.013*** | 0.012*** | 0.009*** |
| | | (3.790) | (3.826) | (3.841) |
| $MOM_{m-1}$ | | -0.012** | -0.010* | -0.008 |
| | | (-2.120) | (-1.910) | (-1.642) |
| $Return_{m-1}$ | | 0.003 | 0.006 | 0.009 |
| | | (0.133) | (0.271) | (0.381) |
| Insider FE | No | No | Yes | Yes |
| Industry FE | No | No | No | Yes |
| # Obs. | 15,452,803 | 14,012,313 | 14,012,313 | 14,012,313 |
| Adj. $R^2$ | 0.001 | 0.002 | 0.018 | 0.018 |

**Panel B: *Cross-Insider Trading* and Direction of Earnings News**

| | (1) $\mathbf{I}_{net\ buy,m}$ | (2) $\mathbf{I}_{net\ buy,m}$ | (3) $\mathbf{I}_{net\ buy,m}$ | (4) $\mathbf{I}_{net\ buy,m}$ |
|---|---|---|---|---|
| $CAR_3$ | 0.070 | 0.088 | 0.087 | 0.087 |
| | (0.925) | (1.180) | (1.169) | (1.166) |
| $\mathbf{I}_{linked,m}$ | 0.249*** | 0.156*** | 0.156*** | 0.155*** |
| | (5.207) | (4.164) | (4.280) | (4.376) |
| $CAR_3 \times \mathbf{I}_{linked,m}$ | 0.502** | 0.482** | 0.479** | 0.485** |
| | (2.443) | (2.176) | (2.179) | (2.303) |
| $lnME_{m-1}$ | | 0.037*** | 0.036*** | 0.035*** |
| | | (6.816) | (6.690) | (6.692) |
| $BM_{m-1}$ | | 0.007*** | 0.007*** | 0.006*** |
| | | (3.820) | (3.873) | (3.997) |
| $MOM_{m-1}$ | | -0.005* | -0.005 | -0.004 |
| | | (-1.735) | (-1.601) | (-1.390) |
| $Return_{m-1}$ | | -0.027* | -0.026 | -0.025 |
| | | (-1.666) | (-1.572) | (-1.547) |
| Insider FE | No | No | Yes | Yes |
| Industry FE | No | No | No | Yes |
| # Obs. | 13,608,394 | 13,515,123 | 13,515,123 | 13,515,123 |
| Adj. $R^2$ | 0.000 | 0.001 | 0.009 | 0.010 |

Table 4 **Return Predictability of *Cross-Insider Order Flows*.** This table presents results of panel regressions of one-week-ahead stock returns on the current week's *cross-insider* and *other order flows*. For Columns (1) and (2), the main independent variables are dollar-amount and share-amount *cross-insider order flows*. For Column (3) and (4), the main independent variables are dollar-amount and share-amount *other order flows*. All regressions include time fixed effects, and control for the last month end's firm size, book-to-market ratio, momentum, and past one-month returns. T-values, reported in parentheses, are based on standard errors clustered at firm and time levels. The sample is from January 2007 to June 2020, and is limited to weeks with at least 15 firms with valid observations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1)<br>$Return_{w+1}$ | (2)<br>$Return_{w+1}$ | (3)<br>$Return_{w+1}$ | (4)<br>$Return_{w+1}$ |
|---|---|---|---|---|
| *cross-insider order flows*$_{\$,w}$ | 0.380*** | | | |
| | (2.853) | | | |
| *cross-insider order flows*$_{share,w}$ | | 0.380*** | | |
| | | (2.823) | | |
| *other order flows*$_{\$,w}$ | | | 0.051 | |
| | | | (1.573) | |
| *other order flows*$_{share,w}$ | | | | 0.050 |
| | | | | (1.543) |
| $lnME_w$ | -0.075 | -0.075 | -0.003 | -0.003 |
| | (-1.241) | (-1.241) | (-0.109) | (-0.110) |
| $MOM_w$ | 0.191 | 0.191 | 0.239*** | 0.239*** |
| | (0.768) | (0.767) | (3.146) | (3.147) |
| $BM_w$ | 0.059 | 0.059 | -0.153** | -0.153** |
| | (0.221) | (0.222) | (-2.236) | (-2.236) |
| $Return_{m-1}$ | -0.735 | -0.734 | -0.469 | -0.470 |
| | (-0.616) | (-0.615) | (-1.206) | (-1.206) |
| Time FE | Yes | Yes | Yes | Yes |
| # Obs. | 7,217 | 7,217 | 51,284 | 51,284 |
| Adj. $R^2$ | 0.236 | 0.236 | 0.266 | 0.266 |

Table 5 **Return Predictability of *Cross-Insider Order Flows* over Different Horizons.** This table shows the results of panel regressions of future two to eight week cumulative returns on *cross-insider order flows*. For Columns (1) to (4), the main independent variables are dollar-amount *cross-insider order flows*. For Columns (5) to (8), the main independent variables are share-amount *cross-insider order flows*. All specifications include time fixed effects, and control for the last month end's firm size, book-to-market ratio, momentum, and past one-month returns. T-values, reported in parentheses, are based on standard errors clustered at firm and time levels. The sample is from January 2007 to June 2020, and is limited to weeks with at least 15 firms with valid observations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | $Return_{w+1:w+2}$ | $Return_{w+1:w+4}$ | $Return_{w+1:w+6}$ | $Return_{w+1:w+8}$ | $Return_{w+1:w+2}$ | $Return_{w+1:w+4}$ | $Return_{w+1:w+6}$ | $Return_{w+1:w+8}$ |
| $Cross\text{-}insider\ order\ flows_{\$,w}$ | 0.495*** | 0.697*** | 0.746*** | 0.905*** | | | | |
| | (2.732) | (3.053) | (2.728) | (3.016) | | | | |
| $Cross\text{-}insider\ order\ flows_{share,w}$ | | | | | 0.487*** | 0.695*** | 0.746*** | 0.901*** |
| | | | | | (2.658) | (3.050) | (2.733) | (3.000) |
| $lnME_w$ | -0.106 | -0.210 | -0.207 | -0.207 | -0.106 | -0.210 | -0.207 | -0.207 |
| | (-1.202) | (-1.406) | (-1.066) | (-0.834) | (-1.200) | (-1.405) | (-1.066) | (-0.834) |
| $MOM_w$ | 0.576* | 1.182** | 1.840** | 2.614** | 0.576* | 1.181** | 1.840** | 2.614** |
| | (1.730) | (1.994) | (2.210) | (2.452) | (1.730) | (1.994) | (2.210) | (2.451) |
| $BM_w$ | -0.231 | -1.162 | -1.398 | -1.921 | -0.231 | -1.162 | -1.397 | -1.920 |
| | (-0.483) | (-1.073) | (-0.817) | (-0.871) | (-0.483) | (-1.072) | (-0.816) | (-0.871) |
| $Return_{m-1}$ | -0.262 | 1.422 | 2.388 | 1.477 | -0.262 | 1.423 | 2.389 | 1.478 |
| | (-0.184) | (0.595) | (0.890) | (0.460) | (-0.185) | (0.595) | (0.890) | (0.460) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| # Obs. | 7,217 | 7,213 | 7,212 | 7,209 | 7,217 | 7,213 | 7,212 | 7,209 |
| Adj. $R^2$ | 0.264 | 0.317 | 0.327 | 0.343 | 0.264 | 0.317 | 0.327 | 0.343 |

Table 6 **Return Predictability of *Cross-Insider Order Flows*: Subsample Analysis.** This table presents results of panel regressions of one-week-ahead stock returns on the current week's *cross-insider order flows* in small firms and large firms subsample. Each week, we classify firms in the bottom size quartile into the group of small firms and classify the remaining firms into the group of large firms. Columns (1) and (2) report results for small firm sample, and Columns (3) and (4) for large firm sample. All regressions include time fixed effects and control for the last month end's firm size, book-to-market ratio, momentum, and past one-month returns. T-values, reported in parentheses, are based on standard errors clustered at firm and time levels. The sample is from January 2007 to June 2020, and is limited to weeks with at least 15 valid observations in the full sample. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | **Sample with Small Firms** | | **Sample with Large Firms** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | $Return_{w+1}$ | $Return_{w+1}$ | $Return_{w+1}$ | $Return_{w+1}$ |
| $\textit{Cross-insider order flows}_{\$,w}$ | 0.787*** | | 0.197 | |
| | (3.141) | | (1.288) | |
| $\textit{Cross-insider order flows}_{share,w}$ | | 0.781*** | | 0.202 |
| | | (3.098) | | (1.310) |
| $lnME_w$ | -0.533** | -0.532** | 0.045 | 0.045 |
| | (-2.425) | (-2.419) | (0.546) | (0.547) |
| $MOM_w$ | -0.066 | -0.066 | 0.351 | 0.351 |
| | (-0.131) | (-0.130) | (1.172) | (1.171) |
| $BM_w$ | 0.839 | 0.841 | -0.269 | -0.269 |
| | (1.267) | (1.268) | (-0.660) | (-0.659) |
| $Return_{m-1}$ | -0.769 | -0.770 | -0.857 | -0.856 |
| | (-0.521) | (-0.522) | (-0.649) | (-0.648) |
| Time FE | Yes | Yes | Yes | Yes |
| # Obs. | 1,813 | 1,813 | 5,404 | 5,404 |
| Adj. $R^2$ | 0.193 | 0.193 | 0.291 | 0.291 |

Table 7 **Likelihood of *Cross-Insider Trading*: Excluding Firms in Insider's Industry or City.** This table examines if insiders are more likely to trade *cross-linked* firms even after excluding firms in insider's own industry or city. For Panel A, we use the sample from Table 2 but exclude firms in insider's own industry. For Panel B, we use the sample from Table 2 but exclude firms in insider's own city. The dependent variable is an indicator equal to one if insider trades the firm in that month, and zero otherwise. We multiply the dependent variable by 100 for coefficient interpretability. The independent variable, $\mathbf{I}_{linked}$, is an indicator equal to one if the firm is *cross-linked* firm to the insider, and zero otherwise. Other control variables include firm size, book-to-market ratio, momentum, and past 1-month return. T-statistics, based on standard errors clustered at insider, firm, and time levels, are reported in parentheses. The sample period is from January 2007 to June 2020. Statistical significance: $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

**Panel A: Exclude Firms in Insider's Industry**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $\mathbf{I}_{trade,m}$ | $\mathbf{I}_{trade,m}$ | $\mathbf{I}_{trade,m}$ | $\mathbf{I}_{trade,m}$ |
| $\mathbf{I}_{linked,m}$ | 0.648*** | 0.374*** | 0.373*** | 0.383*** |
| | (5.725) | (4.226) | (4.314) | (4.514) |
| $lnME_{m-1}$ | | 0.098*** | 0.096*** | 0.090*** |
| | | (8.244) | (8.256) | (8.266) |
| $BM_{m-1}$ | | 0.016*** | 0.015*** | 0.012*** |
| | | (4.518) | (4.642) | (4.747) |
| $MOM_{m-1}$ | | -0.020*** | -0.020*** | -0.016*** |
| | | (-2.978) | (-3.034) | (-2.677) |
| $Return_{m-1}$ | | -0.052** | -0.049* | -0.043* |
| | | (-2.019) | (-1.897) | (-1.715) |
| Insider FE | No | No | Yes | Yes |
| Industry FE | No | No | No | Yes |
| # Obs. | 38,773,238 | 34,013,944 | 34,013,944 | 34,013,944 |
| Adj. $R^2$ | 0.001 | 0.003 | 0.018 | 0.019 |

**Panel B: Exclude Firms in Insider's City**

| | (1) $\mathbf{I}_{trade,m}$ | (2) $\mathbf{I}_{trade,m}$ | (3) $\mathbf{I}_{trade,m}$ | (4) $\mathbf{I}_{trade,m}$ |
|---|---|---|---|---|
| $\mathbf{I}_{linked,m}$ | 0.662*** | 0.430*** | 0.423*** | 0.432*** |
| | (6.134) | (4.919) | (5.029) | (5.076) |
| $lnME_{m-1}$ | | 0.091*** | 0.089*** | 0.089*** |
| | | (8.844) | (8.600) | (8.086) |
| $BM_{m-1}$ | | 0.013*** | 0.013*** | 0.012*** |
| | | (4.478) | (4.539) | (4.619) |
| $MOM_{m-1}$ | | -0.016*** | -0.017*** | -0.016** |
| | | (-2.640) | (-2.692) | (-2.589) |
| $Return_{m-1}$ | | -0.031 | -0.030 | -0.030 |
| | | (-1.413) | (-1.387) | (-1.378) |
| Insider FE | No | No | Yes | Yes |
| Industry FE | No | No | No | Yes |
| # Obs. | 40,369,431 | 35,736,466 | 35,736,466 | 35,736,466 |
| Adj. $R^2$ | 0.001 | 0.003 | 0.019 | 0.019 |

Table 8 **Return Predictability of *Cross-Insider Order Flows*: Excluding Firms in Insider's Industry or City.** This table examines the return predictability of *cross-insider order flows* after excluding trades in firms which are in insider's industry or city. The regressions are based on Table 4 but for Columns (1) and (2), we exclude insiders' trades on firms which are in insider's own industry, and for Columns (3) and (4), we exclude insiders' trades on firms whose headquarters are located in the same city as insider's own city. All regressions include time fixed effects and control for last month end's firm size, book-to-market ratio, momentum, and past one-month returns. T-values, reported in parentheses, are based on standard errors clustered at firm and time levels. The sample is from January 2007 to June 2020, and is limited to weeks with at least 15 firms with valid observations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | **Exclude Firms in Insider's Industry** | | **Exclude Firms in Insider's City** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | $Return_{w+1}$ | $Return_{w+1}$ | $Return_{w+1}$ | $Return_{w+1}$ |
| $cross\text{-}insider\ order\ flows_{\$,w}$ | 0.355** | | 0.458*** | |
| | (2.221) | | (3.217) | |
| $cross\text{-}insider\ order\ flows_{share,w}$ | | 0.355** | | 0.452*** |
| | | (2.218) | | (3.153) |
| $lnME_w$ | -0.070 | -0.070 | -0.065 | -0.065 |
| | (-1.177) | (-1.176) | (-1.102) | (-1.102) |
| $MOM_w$ | 0.190 | 0.190 | 0.190 | 0.190 |
| | (0.762) | (0.762) | (0.764) | (0.764) |
| $BM_w$ | 0.047 | 0.047 | 0.044 | 0.045 |
| | (0.178) | (0.179) | (0.170) | (0.171) |
| $Return_{m-1}$ | -0.777 | -0.777 | -0.763 | -0.763 |
| | (-0.653) | (-0.653) | (-0.639) | (-0.639) |
| Time FE | Yes | Yes | Yes | Yes |
| #Obs. | 7,217 | 7,217 | 7,217 | 7,217 |
| Adj. $R^2$ | 0.235 | 0.235 | 0.236 | 0.236 |

Table 9 **Likelihood of *Reciprocal Cross-insider Trading*** This table examines whether insiders are more likely to trade firms of linked insiders who have profited from trading focal insider' firm. We use the same sample as Table 2. The dependent variable is an indicator equal to one if the insider trades the firm in that month, and zero otherwise. We multiply the dependent variable by 100 for coefficient interpretability. The independent variable, $\mathbf{I}_{linked}$, is an indicator equal to one if the firm is *cross-linked* to the insider, and zero otherwise. $\mathbf{I}_{reciprocal}$ is an indicator equal to one if at least one of linked insider in the firm has profited from trading the focal insider's firm, and zero otherwise. Other control variables include firm size, book-to-market ratio, momentum, and past 1-month return. T-statistics, based on standard errors clustered at insider, firm, and time levels, are reported in parentheses. The sample period is from January 2007 to June 2020. Statistical significance: $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

| | (1) $\mathbf{I}_{trade,m}$ | (2) $\mathbf{I}_{trade,m}$ | (3) $\mathbf{I}_{trade,m}$ | (4) $\mathbf{I}_{trade,m}$ |
|---|---|---|---|---|
| $\mathbf{I}_{linked,m}$ | 0.885*** | 0.568*** | 0.567*** | 0.568*** |
| | (5.663) | (4.346) | (4.394) | (4.490) |
| $\mathbf{I}_{linked,m} \times \mathbf{I}_{reciprocal,m}$ | 0.830*** | 0.797*** | 0.779*** | 0.774*** |
| | (3.954) | (3.922) | (4.008) | (4.063) |
| $lnME_{m-1}$ | | 0.113*** | 0.109*** | 0.105*** |
| | | (7.797) | (7.757) | (7.803) |
| $BM_{m-1}$ | | 0.019*** | 0.018*** | 0.014*** |
| | | (4.260) | (4.306) | (4.335) |
| $MOM_{m-1}$ | | -0.023*** | -0.022*** | -0.019** |
| | | (-2.839) | (-2.756) | (-2.554) |
| $Return_{m-1}$ | | -0.058* | -0.054* | -0.050 |
| | | (-1.885) | (-1.761) | (-1.647) |
| Insider FE | No | No | Yes | Yes |
| Industry FE | No | No | No | Yes |
| #Obs. | 50,463,879 | 44,867,769 | 44,867,769 | 44,867,769 |
| Adj. $R^2$ | 0.002 | 0.004 | 0.025 | 0.025 |

Table 10 **Return Predictability of *Reciprocal Cross-Insider Order Flows*.** This table presents results of panel regressions of one-week-ahead stock returns on the current week's *reciprocal cross-insider order flows*. For Columns (1) and (2), the main independent variables are dollar-amount *reciprocal cross-insider order flows* and *non-reciprocal cross-insider order flows*. The definition of *reciprocal cross-insider order flows* is in Section 4.2, and *non-reciprocal cross-insider order flows* are the scaled aggregated order flows of the remaining *cross-insider trading*. For Columns (3) and (4), independent variables are share-amount *reciprocal cross-insider order flows* and *non-reciprocal cross-insider order flows*. All regressions include time fixed effects, and control for the last month end's firm size, book-to-market ratio, momentum, and past one-month returns. T-values, reported in parentheses, are based on standard errors clustered at firm and time levels. The sample is from January 2007 to June 2020, and is limited to weeks with at least 15 firms with valid observations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1) $Return_{w+1}$ | (2) $Return_{w+1}$ | (3) $Return_{w+1}$ | (4) $Return_{w+1}$ |
|---|---|---|---|---|
| $reciprocal\ cross\text{-}insider\ order\ flows_{\$,w}$ | 1.109*** | | | |
| | (2.764) | | | |
| $non\text{-}reciprocal\ cross\text{-}insider\ order\ flows_{\$,w}$ | | 0.294** | | |
| | | (2.124) | | |
| $reciprocal\ cross\text{-}insider\ order\ flows_{share,w}$ | | | 1.113*** | |
| | | | (2.747) | |
| $non\text{-}reciprocal\ cross\text{-}insider\ order\ flows_{share,w}$ | | | | 0.293** |
| | | | | (2.104) |
| $lnME_w$ | -0.069 | -0.073 | -0.069 | -0.073 |
| | (-1.175) | (-1.203) | (-1.175) | (-1.203) |
| $MOM_w$ | 0.190 | 0.197 | 0.190 | 0.197 |
| | (0.763) | (0.792) | (0.763) | (0.791) |
| $BM_w$ | 0.037 | 0.058 | 0.037 | 0.058 |
| | (0.138) | (0.220) | (0.138) | (0.221) |
| $Return_{m-1}$ | -0.766 | -0.763 | -0.766 | -0.763 |
| | (-0.644) | (-0.637) | (-0.643) | (-0.637) |
| Time FE | Yes | Yes | Yes | Yes |
| #Obs. | 7,217 | 7,217 | 7,217 | 7,217 |
| Adj. $R^2$ | 0.236 | 0.235 | 0.236 | 0.235 |

Table 11 **Profitability of *Cross-Insider Trading* and Linked Insider *Moving Out*.** This table examines, using a difference-in-differences (DID) setting, whether the profitability of *cross-insider trading* declines after a linked insider's "*moving out*" event (formally defined in Section 4.3). The sample includes trades in the affected firm and in same-industry control firms. The dependent variable is the future 20-day DGTW-adjusted cumulative abnormal return, multiplied by +1 for buy trades and -1 for sell trades. The independent variable $\mathbf{I}_{linked}$ is the *cross-linked* dummy as before. *Post* is an indicator equal to one if the trade is after the "*moving out*". $T_{y-2}$ ($T_{y-3}$) is an indicator equal to one if the trade happens in the second (third) year prior to the "*moving out*". All models include stock and time fixed effects, and control for the last month end's firm size, book-to-market ratio, momentum, and past one-month returns. T-values are in parentheses, with standard errors clustered at insider and stock levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

| | (1) $CAR_{20}$ | (2) $CAR_{20}$ | (3) $CAR_{20}$ | (4) $CAR_{20}$ |
|---|---|---|---|---|
| $\mathbf{I}_{linked,m}$ | 0.854** | 0.877** | 1.234* | 1.274* |
| | (2.016) | (2.025) | (1.885) | (1.931) |
| $Post_m$ | 0.461*** | 0.453*** | 0.369** | 0.364** |
| | (3.363) | (3.263) | (2.322) | (2.227) |
| $\mathbf{I}_{linked,m} \times Post_m$ | -1.218** | -1.250** | -1.584** | -1.633** |
| | (-2.176) | (-2.184) | (-2.053) | (-2.101) |
| $T_{y-2}$ | | | -0.222 | -0.199 |
| | | | (-0.927) | (-0.815) |
| $\mathbf{I}_{linked,m} \times T_{y-2}$ | | | -1.356 | -1.389 |
| | | | (-0.973) | (-1.008) |
| $T_{y-3}$ | | | -0.994** | -1.000** |
| | | | (-2.182) | (-2.205) |
| $\mathbf{I}_{linked,m} \times T_{y-3}$ | | | -0.812 | -0.962 |
| | | | (-0.620) | (-0.743) |
| $lnME_{m-1}$ | | -0.427 | | -0.426 |
| | | (-1.456) | | (-1.450) |
| $BM_{m-1}$ | | 0.520* | | 0.531* |
| | | (1.722) | | (1.757) |
| $MOM_{m-1}$ | | -0.082 | | -0.073 |
| | | (-0.375) | | (-0.335) |
| $Return_{m-1}$ | | -1.179 | | -1.159 |
| | | (-1.524) | | (-1.496) |
| Time FE | Yes | Yes | Yes | Yes |
| Stock FE | Yes | Yes | Yes | Yes |
| # Obs. | 25,910 | 25,910 | 25,910 | 25,910 |
| Adj. $R^2$ | 0.050 | 0.051 | 0.050 | 0.051 |

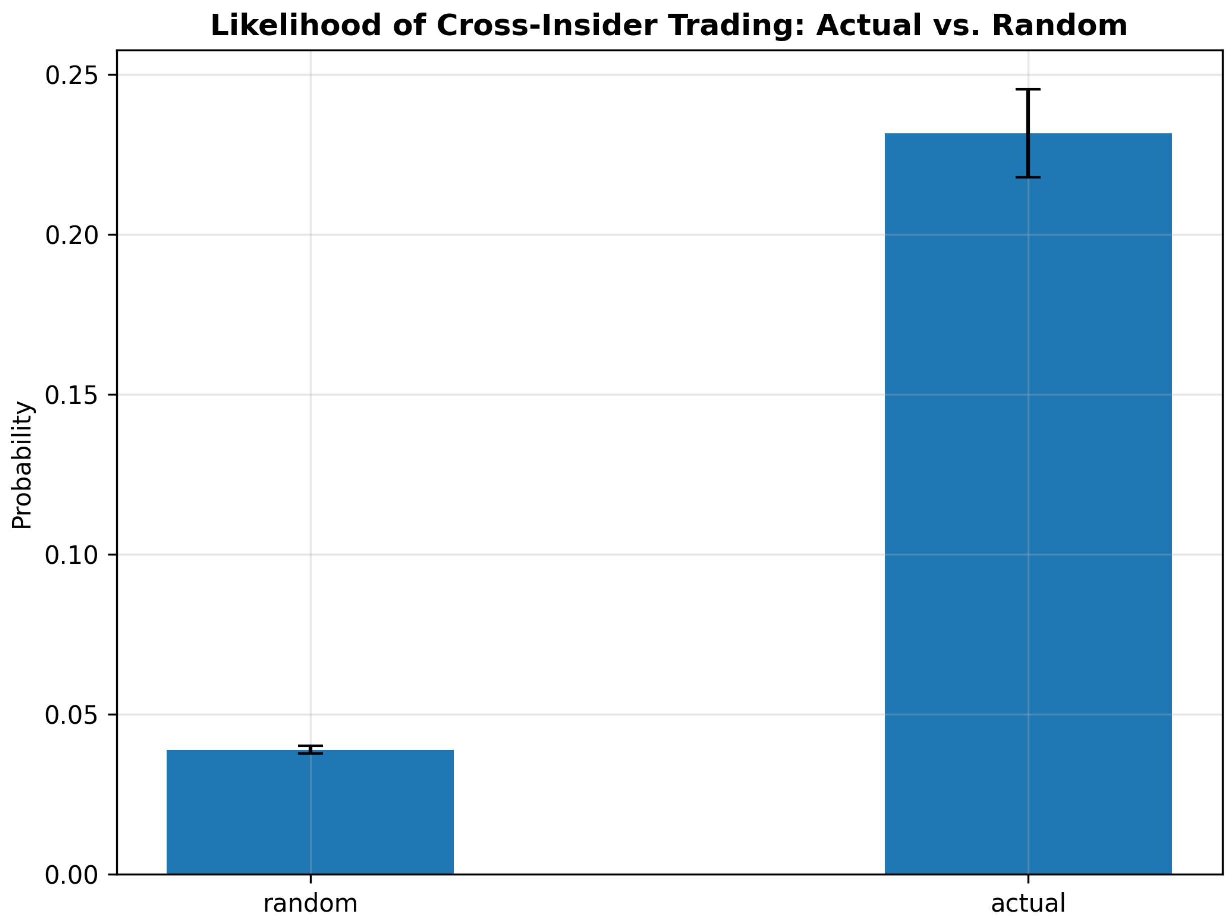


Figure 1: Likelihood of *Cross-Insider Trading*: Actual vs. Random Benchmark.

This figure compares the observed probability of *cross-insider trading* against a random benchmark. Specifically, the "random" probability refers to the likelihood of selecting the *cross-linked* firm from a set of all firms in its industry (excluding insider's own firm), each of which has an equal probability of being chosen. The "actual" bar shows the average observed probability of trading a *cross-linked* firms across insiders. The "random" bar shows the average "random" probability of trading *cross-linked* firms across insiders. Error bars indicate 99% confidence intervals.

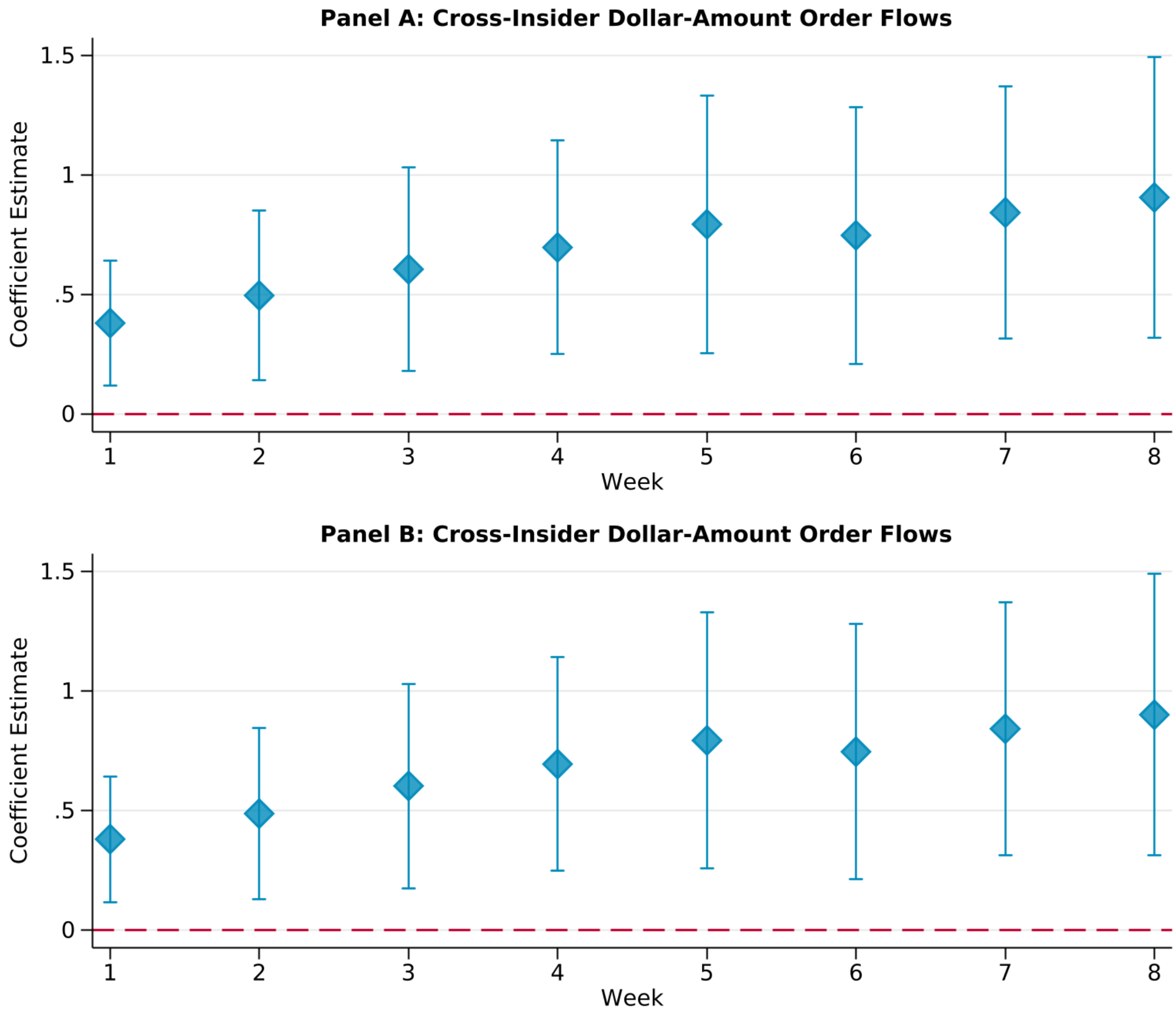


Figure 2: **Dynamics of Return Predictability of *Cross-Insider Order Flows*.** This figure plots the coefficient estimates and their 95% confidence intervals from panel regressions of future weekly returns on insider order flow. The x-axis represents the future return horizon in weeks, from future one week to eight weeks. The top panel shows results for the dollar-amount *cross-insider order flows*, and the bottom panel shows results for the share-amount *cross-insider order flows*. All regressions control for the last month end's firm size, book-to-market ratio, momentum, and past one-month returns, and include time fixed effects. Standard errors are clustered at firm and time levels. The sample is from January 2007 to June 2020, and is limited to weeks with at least 15 firms with valid observations.


Figure 3: **Dynamics of Return Predictability of *Reciprocal Cross-Insider Order Flows*.** This figure plots the coefficient estimates and their 90% confidence intervals of panel regressions of future weekly returns on *reciprocal* and *non-reciprocal cross-insider order flows*. The x-axis represents the future return horizon in weeks, from future one week to eight weeks. The blue series shows results for the *reciprocal cross-insider order flows*, and the red series shows results for *non-reciprocal cross-insider order flows*. Panel A is for dollar-amount *cross-insider order flows*, and Panel B is for share-amount *cross-insider order flows*.The definitions of the two order flows are in Section 4.2. All regressions control for the last month end's firm size, book-to-market ratio, momentum, and past one-month returns, and include time fixed effects. Standard errors are clustered at firm and time levels. The sample is from January 2007 to June 2020, and is limited to weeks with at least 15 firms with valid observations.

# APPENDIX

## A Additional Results and Robustness Tests

Table A.1 **Fraction of Trading Amount of *Cross-Insider Trading*.** This table examines whether the fraction of trading amount in the *cross-linked* firms are higher. The sample is the same as Table 2. The dependent variable is the insider's dollar trading amount in the firm divided by the total dollar trading amount of the insider in that month. We multiply the dependent variable by 100 for coefficient interpretability. The independent variable, $\mathbf{I}_{linked}$, is an indicator equal to one if the firm is *cross-linked* to the insider. Other control variables include firm size, book-to-market ratio, momentum, and past 1-month return. T-statistics, based on standard errors clustered at insider, firm, and time levels, are reported in parentheses. The sample period is from January 2007 to June 2020. Statistical significance: $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $trading\ fraction_{\$,m}$ | $trading\ fraction_{\$,m}$ | $trading\ fraction_{\$,m}$ | $trading\ fraction_{\$,m}$ |
| $\mathbf{I}_{linked,m}$ | 0.287*** | 0.231*** | 0.231*** | 0.231*** |
| | (4.764) | (4.214) | (4.221) | (4.258) |
| $lnME_{m-1}$ | | 0.020*** | 0.020*** | 0.018*** |
| | | (6.146) | (6.310) | (6.272) |
| $BM_{m-1}$ | | 0.003*** | 0.003*** | 0.002*** |
| | | (3.703) | (3.708) | (3.490) |
| $MOM_{m-1}$ | | -0.005** | -0.004** | -0.004** |
| | | (-2.251) | (-2.162) | (-1.982) |
| $Return_{m-1}$ | | -0.015** | -0.014** | -0.013** |
| | | (-2.173) | (-2.124) | (-2.088) |
| Insider FE | No | No | Yes | Yes |
| Industry FE | No | No | No | Yes |
| # Obs. | 50,463,879 | 44,867,769 | 44,867,769 | 44,867,769 |
| Adj. $R^2$ | 0.001 | 0.002 | 0.004 | 0.004 |

Table A.2 **Return Predictability of *Cross-Insider Trading*: Fama-Macbeth Regression** This table presents results of Fama-Macbeth regressions of one-week-ahead stock returns on the current week's *cross-insider* and *other order flows*. For Columns (1) and (2), the main independent variables are dollar-amount and share-amount *cross-insider order flows*. For Column (3) and (4), the main independent variables are dollar-amount and share-amount *other order flows*. All regressions control for the last month end's firm size, book-to-market ratio, momentum, and past one-month returns. T-values, reported in parentheses, are based on standard errors adjusted for autocorrelation using the Newey-West procedure with 6 lags. The sample is from January 2007 to June 2020, and is limited to weeks with at least 15 firms with valid observations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1)<br>$Return_{w+1}$ | (2)<br>$Return_{w+1}$ | (3)<br>$Return_{w+1}$ | (4)<br>$Return_{w+1}$ |
|---|---|---|---|---|
| $Cross\text{-}insider\ order\ flow_{\$,w}$ | 0.351** | | | |
| | (2.341) | | | |
| $Cross\text{-}insider\ order\ flow_{share,w}$ | | 0.351** | | |
| | | (2.361) | | |
| $Other\ order\ flow_{\$,w}$ | | | 0.072 | |
| | | | (1.634) | |
| $Other\ order\ flow_{share,w}$ | | | | 0.071 |
| | | | | (1.613) |
| $lnME_w$ | -0.135** | -0.136** | -0.014 | -0.014 |
| | (-2.533) | (-2.546) | (-0.562) | (-0.567) |
| $MOM_w$ | 0.471* | 0.469* | 0.280 | 0.280 |
| | (1.760) | (1.756) | (1.496) | (1.495) |
| $BM_w$ | 0.213 | 0.216 | -0.068 | -0.068 |
| | (0.580) | (0.590) | (-0.521) | (-0.525) |
| $Return_{m-1}$ | -0.065 | -0.058 | -0.488 | -0.489 |
| | (-0.067) | (-0.060) | (-1.187) | (-1.188) |
| # Obs. | 7,217 | 7,217 | 51,284 | 51,284 |
| Adj. $R^2$ | 0.152 | 0.152 | 0.106 | 0.106 |

Table A.3 **Return Predictability of *Cross-Insider Trading* with Alternative Sample Filters.** This table presents results of panel regressions of one-week-ahead stock returns on the current week's *cross-insider* and *other order flows* with different sample filters. Specifically, for Columns (1) and (2), we adopt the filter keeping weeks with at least 10 firms with valid observations, and the threshold for Columns (3) and (4) is 12, and that for Columns (5) and (6) is 12, and that for Columns (7) and (8) is 20. The main independent variables are dollar-amount and share-amount *cross-insider order flows*. All regressions include time fixed effects, and control for the last month end's firm size, book-to-market ratio, momentum, and past one-month returns. T-values, reported in parentheses, are based on standard errors clustered at firm and time levels. The sample is from January 2007 to June 2020. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | **nobs $\geq$ 10** | | **nobs $\geq$ 12** | | **nobs $\geq$ 18** | | **nobs $\geq$ 20** | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | $Return_{w+1}$ | $Return_{w+1}$ | $Return_{w+1}$ | $Return_{w+1}$ | $Return_{w+1}$ | $Return_{w+1}$ | $Return_{w+1}$ | $Return_{w+1}$ |
| *Cross-insider order flow*$_{\$,w}$ | 0.317*** | | 0.324** | | 0.386*** | | 0.309** | |
| | (2.669) | | (2.578) | | (2.730) | | (2.262) | |
| *Cross-insider order flow*$_{share,w}$ | | 0.316*** | | 0.323** | | 0.385*** | | 0.310** |
| | | (2.640) | | (2.546) | | (2.700) | | (2.238) |
| $lnME_w$ | -0.076 | -0.076 | -0.080 | -0.080 | -0.060 | -0.060 | -0.034 | -0.034 |
| | (-1.314) | (-1.313) | (-1.316) | (-1.316) | (-0.998) | (-0.998) | (-0.585) | (-0.585) |
| $MOM_w$ | 0.070 | 0.070 | 0.063 | 0.063 | 0.151 | 0.151 | 0.099 | 0.099 |
| | (0.309) | (0.309) | (0.270) | (0.269) | (0.578) | (0.578) | (0.356) | (0.356) |
| $BM_w$ | -0.101 | -0.101 | -0.015 | -0.015 | -0.114 | -0.114 | -0.136 | -0.136 |
| | (-0.401) | (-0.400) | (-0.058) | (-0.058) | (-0.501) | (-0.500) | (-0.663) | (-0.662) |
| $Return_{m-1}$ | -0.415 | -0.415 | -0.427 | -0.427 | -0.741 | -0.741 | -0.537 | -0.536 |
| | (-0.368) | (-0.368) | (-0.366) | (-0.366) | (-0.600) | (-0.600) | (-0.409) | (-0.408) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| # Obs. | 8,152 | 8,152 | 7,641 | 7,641 | 6,741 | 6,741 | 6,141 | 6,141 |
| Adj. $R^2$ | 0.240 | 0.240 | 0.239 | 0.239 | 0.230 | 0.230 | 0.228 | 0.228 |

Table A.4 **Holdings-based Calendar-time Performance of *Cross-Insider Trading*** This table reports the performance of holdings-based calendar-time portfolios of *cross-insider trading*, *other trading* and their difference. The daily holding positions are constructed using calendar-time purchase and sell transaction records, and returns are holdings-value-weighted and expressed at basis-points. The rows "DGTW", and "Excess" report the DGTW-adjusted return, and excess return, respectively, while "CAPM", "FF3", and "FFC4" report $\alpha$ under CAPM, Fama-French 3-factors, and Fama-French 3-factors augmented by an additional momentum factor, respectively. T-values of the difference, reported in parentheses in the last column, are adjusted for autocorrelation using the Newey-West procedure with 6 lags. The Statistical significance: $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

| | **Cross** | **Others** | **Diff** | **t-stat** |
|---|---|---|---|---|
| **Excess** | 9.854 | 4.154 | 4.454 | (2.50) |
| **CAPM** | 7.179 | 2.584 | 4.313 | (2.43) |
| **FF3** | 7.241 | 2.657 | 4.344 | (2.45) |
| **FFC4** | 8.148 | 3.882 | 4.137 | (2.35) |
| **DGTW** | 5.052 | 1.533 | 3.278 | (2.16) |

Table A.5 **Fraction of Trading Amount of *Reciprocal Cross-Insider Trading*.** This table examines whether the fraction of trading amount in the *reciprocal cross-linked* firms are higher. The sample is the same as Table 9. The dependent variable is the insider's dollar trading amount in the firm divided by the total dollar trading amount of the insider in that month. We multiply the dependent variable by 100 for coefficient interpretability. The independent variable, $\mathbf{I}_{linked}$, is an indicator equal to one if the firm is *cross-linked* to the insider. $\mathbf{I}_{reciprocal}$ is an indicator equal to one if at least one linked insider of the firm has profited from trading on the focal insider's own firm. Other control variables include firm size, book-to-market ratio, momentum, and past 1-month return. T-statistics, based on standard errors clustered at insider, firm, and time levels, are reported in parentheses. The sample period is from January 2007 to June 2020. Statistical significance: $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

| | (1)<br>$trading\ fraction_{\$,m}$ | (2)<br>$trading\ fraction_{\$,m}$ | (3)<br>$trading\ fraction_{\$,m}$ | (4)<br>$trading\ fraction_{\$,m}$ |
|---|---|---|---|---|
| $\mathbf{I}_{linked,m}$ | 0.263*** | 0.208*** | 0.208*** | 0.208*** |
| | (4.958) | (4.328) | (4.330) | (4.360) |
| $\mathbf{I}_{linked,m} \times \mathbf{I}_{reciprocal,m}$ | 0.169** | 0.163** | 0.164** | 0.163** |
| | (2.215) | (2.123) | (2.156) | (2.164) |
| $lnME_{m-1}$ | | 0.020*** | 0.019*** | 0.018*** |
| | | (6.177) | (6.331) | (6.287) |
| $BM_{m-1}$ | | 0.003*** | 0.003*** | 0.002*** |
| | | (3.712) | (3.708) | (3.487) |
| $MOM_{m-1}$ | | -0.004** | -0.004** | -0.004* |
| | | (-2.241) | (-2.153) | (-1.972) |
| $Return_{m-1}$ | | -0.015** | -0.014** | -0.013** |
| | | (-2.162) | (-2.112) | (-2.079) |
| Insider FE | No | No | Yes | Yes |
| Industry FE | No | No | No | Yes |
| #Obs. | 50,463,879 | 44,867,769 | 44,867,769 | 44,867,769 |
| Adj. $R^2$ | 0.001 | 0.002 | 0.004 | 0.004 |

Table A.6 **Profitability of *Cross-Insider Trading* and Linked Insider *Moving Out*: Alternative Window Length.** This table re-examines whether the profitability of *cross-insider trading* declines after a linked insider's "*moving out*" event (formally defined in Section 4.3) under different window lengths. For Columns (1) to (4), we use a 24-month window length. For Columns (5) to (8), we use a 30-month window length. The sample includes trades in the affected firm and in same-industry control firms. The dependent variable is the future 20-day DGTW-adjusted cumulative abnormal return, multiplied by +1 for buy trades and -1 for sell trades. The independent variable $\mathbf{I}_{linked}$ is the *cross-linked* dummy as before. *Post* is an indicator equal to one if the trade is after the "*moving out*". $T_{y-2}$ ($T_{y-3}$) is an indicator equal to one if the trade happens in the second (third) year prior to the "*moving out*". All models include stock and time fixed effects, and control for the last month end's firm size, book-to-market ratio, momentum, and past one-month returns. T-values are in parentheses, with standard errors clustered at insider and stock levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

| | Window length = 24 months | | | | Window length = 30 months | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | $CAR_{20}$ | $CAR_{20}$ | $CAR_{20}$ | $CAR_{20}$ | $CAR_{20}$ | $CAR_{20}$ | $CAR_{20}$ | $CAR_{20}$ |
| $\mathbf{I}_{linked,m}$ | 0.817** | 0.821** | 1.033** | 1.033* | 0.754** | 0.787** | 1.150* | 1.189** |
| | (2.111) | (2.100) | (1.965) | (1.959) | (2.018) | (2.055) | (1.930) | (1.981) |
| $Post_m$ | 0.307*** | 0.296** | 0.297** | 0.289** | 0.508*** | 0.489*** | 0.481*** | 0.467*** |
| | (2.611) | (2.523) | (2.191) | (2.131) | (3.982) | (3.736) | (3.441) | (3.239) |
| $\mathbf{I}_{linked,m} \times Post_m$ | -1.334*** | -1.292*** | -1.547*** | -1.501** | -1.203** | -1.205** | -1.593** | -1.601** |
| | (-2.984) | (-2.907) | (-2.635) | (-2.576) | (-2.377) | (-2.334) | (-2.269) | (-2.259) |
| $T_{y-2}$ | | | -0.046 | -0.036 | | | -0.002 | 0.013 |
| | | | (-0.228) | (-0.180) | | | (-0.009) | (0.058) |
| $\mathbf{I}_{linked,m} \times T_{y-2}$ | | | -0.792 | -0.778 | | | -1.463 | -1.468 |
| | | | (-0.789) | (-0.787) | | | (-1.209) | (-1.232) |
| $T_{y-3}$ | | | | | | | -0.919* | -0.862 |
| | | | | | | | (-1.723) | (-1.645) |
| $\mathbf{I}_{linked,m} \times T_{y-3}$ | | | | | | | -0.327 | -0.432 |
| | | | | | | | (-0.271) | (-0.360) |
| $lnME_{m-1}$ | | -0.491** | | -0.488** | | -0.553* | | -0.545* |
| | | (-2.087) | | (-2.076) | | (-1.885) | | (-1.847) |
| $BM_{m-1}$ | | 0.064 | | 0.067 | | 0.331 | | 0.334 |
| | | (0.249) | | (0.260) | | (0.931) | | (0.940) |
| $MOM_{m-1}$ | | 0.068 | | 0.069 | | 0.105 | | 0.102 |
| | | (0.311) | | (0.314) | | (0.471) | | (0.460) |
| $Return_{m-1}$ | | -0.860 | | -0.859 | | -0.477 | | -0.460 |
| | | (-1.211) | | (-1.209) | | (-0.566) | | (-0.545) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| #Obs | 32,646 | 32,646 | 32,646 | 32,646 | 29,173 | 29,173 | 29,173 | 29,173 |
| Adj. $R^2$ | 0.042 | 0.043 | 0.042 | 0.043 | 0.060 | 0.061 | 0.060 | 0.061 |

Table A.7 **Profitability of *Cross-Insider Trading* and Linked Insider *Moving Out*: Alternative Event Filter.** This table re-examines whether the profitability of *cross-insider trading* declines after a linked insider's "*moving out*" event, after including events where the focal insider is connected to the linked firm via multiple insiders. For multiple-linked-insider events, we define "*moving out month*" as the last leaving time among all linked insiders. For Columns (1) to (4), we use a 24-month window length. For Columns (5) to (8), we use a 30-month window length. For Columns (9) to (12), we use a 36-month window length. The sample includes trades in the affected firm and in same-industry control firms. The dependent variable is the future 20-day DGTW-adjusted cumulative abnormal return, multiplied by +1 for buy trades and -1 for sell trades. The independent variable $\mathbf{I}_{linked}$ is the *cross-linked* dummy as before. *Post* is an indicator equal to one if the trade is after the "*moving out*". $T_{y-2}$ ($T_{y-3}$) is an indicator equal to one if the trade happens in the second (third) year prior to the "*moving out*". All models include stock and time fixed effects, and control for the last month end's firm size, book-to-market ratio, momentum, and past one-month returns. T-values are in parentheses, with standard errors clustered at insider and stock levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

| | Window length = 24 months | | | | Window length = 30 months | | | | Window length = 36 months | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) $CAR_{20}$ | (2) $CAR_{20}$ | (3) $CAR_{20}$ | (4) $CAR_{20}$ | (5) $CAR_{20}$ | (6) $CAR_{20}$ | (7) $CAR_{20}$ | (8) $CAR_{20}$ | (9) $CAR_{20}$ | (10) $CAR_{20}$ | (11) $CAR_{20}$ | (12) $CAR_{20}$ |
| $\mathbf{I}_{linked,m}$ | 0.635* | 0.634* | 0.891* | 0.882* | 0.673* | 0.701* | 1.068* | 1.102* | 0.849** | 0.867** | 1.201* | 1.234** |
| | (1.796) | (1.773) | (1.856) | (1.824) | (1.853) | (1.865) | (1.893) | (1.925) | (2.068) | (2.074) | (1.935) | (1.973) |
| $Post_m$ | 0.258** | 0.243** | 0.272** | 0.258* | 0.432*** | 0.410*** | 0.420*** | 0.402*** | 0.372*** | 0.360** | 0.294* | 0.288* |
| | (2.194) | (2.059) | (2.072) | (1.965) | (3.275) | (3.015) | (2.957) | (2.739) | (2.623) | (2.475) | (1.864) | (1.751) |
| $\mathbf{I}_{linked,m} \times Post_m$ | -0.952** | -0.903** | -1.211** | -1.154** | -1.151** | -1.137** | -1.539** | -1.531** | -1.135** | -1.135** | -1.477** | -1.493** |
| | (-2.423) | (-2.287) | (-2.281) | (-2.175) | (-2.394) | (-2.306) | (-2.342) | (-2.290) | (-2.192) | (-2.151) | (-2.089) | (-2.092) |
| $T_{y-2}$ | | | 0.051 | 0.054 | | | 0.085 | 0.090 | | | -0.130 | -0.114 |
| | | | (0.279) | (0.294) | | | (0.397) | (0.419) | | | (-0.605) | (-0.522) |
| $\mathbf{I}_{linked,m} \times T_{y-2}$ | | | -0.860 | -0.831 | | | -1.476 | -1.476 | | | -1.383 | -1.409 |
| | | | (-0.988) | (-0.970) | | | (-1.288) | (-1.303) | | | (-1.044) | (-1.074) |
| $T_{y-3}$ | | | | | | | -0.924** | -0.843* | | | -0.987** | -0.944** |
| | | | | | | | (-1.994) | (-1.814) | | | (-2.459) | (-2.308) |
| $\mathbf{I}_{linked,m} \times T_{y-3}$ | | | | | | | -0.125 | -0.239 | | | -0.258 | -0.409 |
| | | | | | | | (-0.117) | (-0.225) | | | (-0.211) | (-0.341) |
| $lnME_{m-1}$ | | -0.556** | | -0.554** | | -0.525* | | -0.520* | | -0.393 | | -0.395 |
| | | (-2.289) | | (-2.282) | | (-1.891) | | (-1.867) | | (-1.421) | | (-1.431) |
| $BM_{m-1}$ | | 0.100 | | 0.104 | | 0.338 | | 0.331 | | 0.484 | | 0.479 |
| | | (0.388) | | (0.403) | | (1.024) | | (1.000) | | (1.549) | | (1.513) |
| $MOM_{m-1}$ | | 0.166 | | 0.164 | | 0.176 | | 0.173 | | 0.020 | | 0.025 |
| | | (0.748) | | (0.737) | | (0.798) | | (0.784) | | (0.088) | | (0.111) |
| $Return_{m-1}$ | | -0.984 | | -0.980 | | -0.583 | | -0.560 | | -1.300* | | -1.271* |
| | | (-1.484) | | (-1.479) | | (-0.717) | | (-0.688) | | (-1.769) | | (-1.726) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| #Obs | 35,343 | 35,343 | 35,343 | 35,343 | 31,424 | 31,424 | 31,424 | 31,424 | 28,078 | 28,078 | 28,078 | 28,078 |
| Adj. $R^2$ | 0.042 | 0.042 | 0.042 | 0.042 | 0.056 | 0.057 | 0.057 | 0.057 | 0.049 | 0.050 | 0.049 | 0.050 |

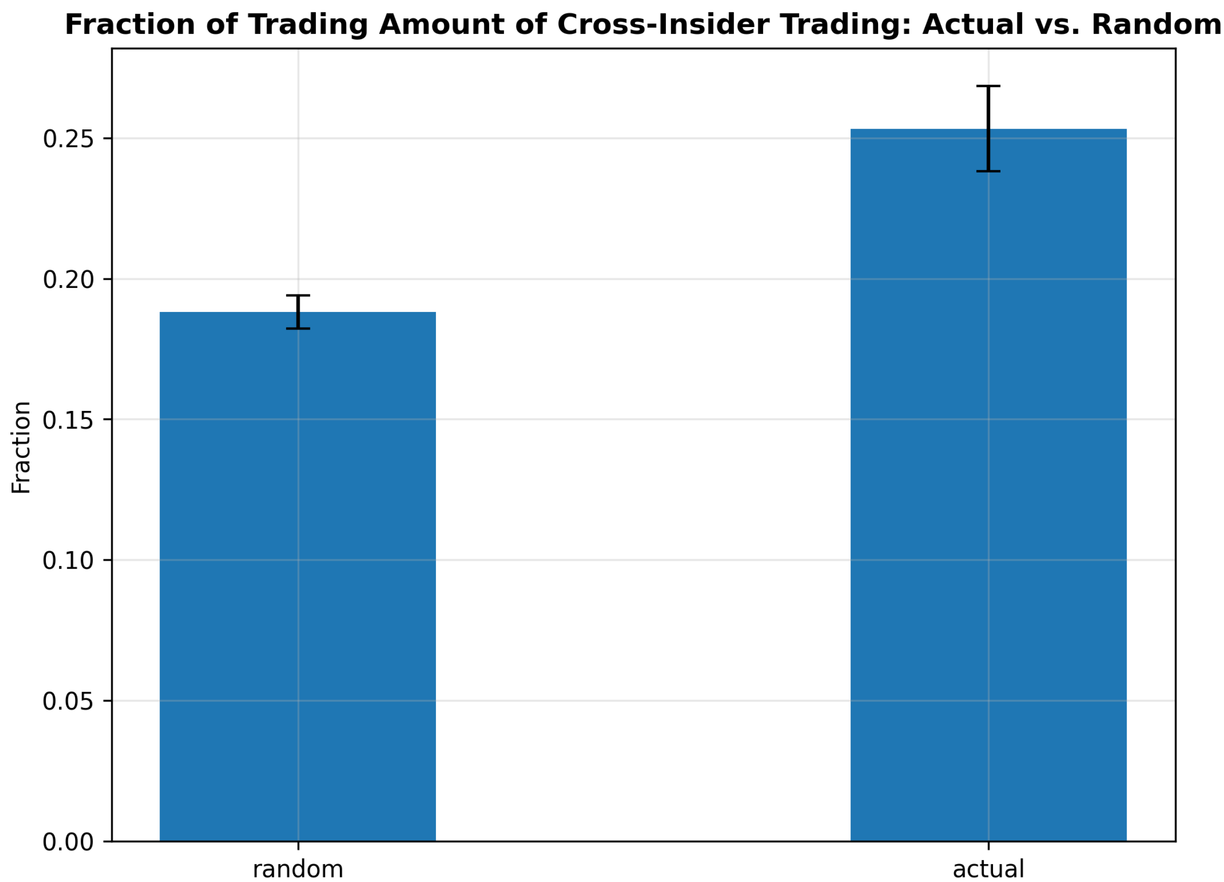


Figure A.1: Fraction of Trading Amount of *Cross-Insider Trading*: Actual vs. Random Benchmark.

This figure compares the observed fraction of trading amount of *cross-insider trading* against a random benchmark. Specifically, the "random" trading fraction is defined as the probability of selecting it in a probability-weighted random draw from all firms in the same industry (excluding insider's own firm), with probabilities proportional to their market capitalizations. The "actual" bar shows the average observed fraction of trading amount of *cross-insider trading*. The "random" bar shows the average "random" trading fraction across insiders. Error bars indicate 99% confidence intervals.