Institutional Investor Cliques Information Dissemination, and the Value of Information: Evidence from Insider Trading

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ABSTRACT

I analyze the relationship between insider trading outcomes and insiders' information environment within a network. While most existing studies rely on one dimension of commonality (e.g., personal ties, professional ties, geographic proximity) to construct the social network, I document the formation of the institutional investor groups (cliques) that exogenously connect firm-level insiders within the social network. Using difference-in-differences designs examining changes in clique size, I provide empirical evidence on the information dissemination channels within a network in which its members are quasi-randomly selected. Insider transactions in larger cliques exhibit lower abnormal trading profits, higher level of trading frequency, and larger amount of trade size, suggesting information dissemination is increasing in clique size. Then, I provide empirical evidence that the association between the value of information and the information dissemination rate is monotonic, consistent with prior theoretical studies.

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GENERAL AUDIENCE ABSTRACT

People communicate and are influenced by other people when they reside in a social network. I analyze how corporate insiders' trading outcomes are influenced by their information environment within a network. Most current research rely on one specific type of connection (e.g., personal relationships, professional relationships, geographic proximity) to build the social network, I provide evidence that firm-level insiders are involuntarily connected by the institutional investor social network (cliques). Using archival study approach, I document that insider transactions in larger cliques exhibit lower abnormal trading profits, higher level of trading frequency, and larger amount of trade size, suggesting information dissemination is increasing in clique size. Then, I provide empirical evidence that the association between the value of information and the information dissemination rate is linear, consistent with prior theoretical studies.

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CHAPTER ONE

INTRODUCTION

1.1 Introduction

The dissemination of information through social networks is critical for financial outcomes (Stein 2008; Han and Yang 2013; Andrei and Cujean 2017). However, empirically identifying the information dissemination process via social networks is challenging because proxies reflecting social interactions can also reflect homophily.[1] Broadly, social network proxies based on commonality might reflect personal or professional information exchange, but investors with similar backgrounds may also act alike absent information exchange. Social connections that may initially appear exogenous can be generated endogenously and serve effectively as proxies for unobserved individual preferences rather than information exchange (Kossinets and Watts 2009).[2] Additionally, indirect proxies that utilize social ties based on commonality cannot disentangle the value of information that investors disseminate. The information could be news reported in public media, uninformed traders' random ideas, or informed investors' private knowledge. Variation in information quality is possible to have different applications for investors' returns.

In this study, I use the properties of institutional investor cliques to examine: 1) whether plausibly exogenous changes in network positions influence corporate insiders' firm-level information environment, reflected in their trades' abnormal returns; and 2) whether faster

[1] "Homophily is the principle that a contact between similar people occurs at a higher rate than among dissimilar people" (McPherson, Smith-Lovin and Cook 2001). Existing evidence relies on proxies such as education background (Cohen, Frazzini and Malloy 2008; 2010), employment connections (Hvide and Ostberg 2015), stock trading correlations (Ozsoylev, Walden, Yavuz and Bildark 2014), and geographic cluster (Hong, Kubik and Stein 2004; Brown, Ivkovic, Smith and Weisbenner 2008).

[2] For example, when two directors both provide specific feedback or make negative comments about a company and subsequently sell their shares, this could be due to both receiving private information about the company through the network (information dissemination) or them reaching the same conclusion independently (homophily). Proxies such as educational ties used in prior research could just capture homophily, rather than personal social network information exchange.

information dissemination is more or less valuable, reflected in insiders' abnormal trading returns and trading patterns. Though sharing private information does not represent all forms of information dissemination, this setting provides several advantages. First, I utilize a social network measure that exogenously connects members within a social network and provides evidence of the information dissemination within a network. More specifically, I examine the relation between institutional investor networks and private information exchange measured by the abnormal profits of corporate insiders' trades based on their belonging to networks of institutional investor cliques. A clique is a cluster of institutions where each member is interconnected to other members via common investments (Crane, Koch and Michenaud 2019). The formation of institutional investor cliques is likely independent from firm-level executives or directors' preference to connect. Corporate insiders may have the ability to influence who invests in their firm, but it is unlikely they can influence the formation of cliques.[3] Since establishing connections utilizing this proxy does not rely on the assumption that insiders share similar backgrounds in any specific dimension, this proxy reflects information exchange but less likely reflects unobserved individual preferences.

Second, I provide empirical evidence that the relation between the value of information and the information dissemination rate is monotonic, in a setting where market participants hold private material information that is less subject to noise or outside influence compared to settings utilized by prior studies (for example, drug approval). Results from theoretical and empirical research does not consistently indicate whether faster dissemination of information is more or less valuable (Han and Yang 2013; Manela 2014). For example, faster dissemination leads to a faster realization of profits that are less subject to noise. Private information may also be more quickly

[3] Azar, Schmalz, and Tecu 2018 find empirical support that large institutions may alter individual firm behavior and have tendencies for holding competitors for diversification. However, Crane et al. 2019 argue large investors (e.g., Blackrock) are less possible to reside in cliques.

reflected in the price, allowing for more predictable profits. However, all informed agents may trade more aggressively in stocks with more efficiently disseminated private information, thus reducing the equilibrium value of information (Manela 2014). Prior empirical studies use indirect proxies such as media coverage for the information dissemination rate. Faster information dissemination could be attributed to the materiality of the information, the level of media coverage, or the attention generated by the topic. This study focuses on the corporate insiders who possess material private information, and specifically on the subset of insiders who tend to trade profitably – opportunistic insiders – and analyzes these insiders' abnormal trading profits and patterns while focuses on opportunistic insiders' behavior when they are exogenously placed in institutional investor cliques. Opportunistic insiders have access to material, nonpublic information while exhibiting a general tendency to trade profitably (Ali and Hirshleifer 2017). This study attempts to exclude immaterial, irrelevant, or public information, disentangling the value of private information and coverage of the public news. I argue these findings are less likely influenced by the investor sentiment and abnormal returns towards irrelevant, public information as well as information dissemination effects caused by a higher or lower level of media coverage and attention.

To capture insiders' access and propensity to exploit the information within a social network, I apply network analysis and graph theory to map institutional investors' cliques through institutional investors' common corporate ownership connections. The term 'insider' refers to corporate officers who must disclose their trading activity on SEC Form 4 (Ali and Hirshleifer 2017; Davidson and Pirinsky 2022), often referred to as insiders or Section 16 insiders. A clique is a cluster of institutions in which members are interconnected, demonstrating the property of high clustered communities. Following Crane, Koch, and Michenaud 2019, I consider two institutions within the network as interconnected if both institutions have an ownership stake of more than 5%. An institutional investor clique is a cluster of institutions in which members are interconnected to other members. Firm-level insiders are corporate executives, directors and beneficiary owners at the firm level.

I consider two channels through which insider transactions' abnormal returns could be influenced by institutional investor cliques – public signaling and information dissemination. Insider transactions, particularly insider purchases, reflect managers' public signaling about their belief in information associated with prospective equity returns (e.g., Jaffe 1974; Finnerty 1976; Seyhun 1986, 1988) and prospective cash flows (Piotroski and Roulstone 2005; Roulstone 2008). Disclosures of insider purchases on SEC Form 4 trigger more positive market reactions and economically significant belief revisions about the firm (Veenman 2012; Brochet 2010).

Material, private information is often disseminated from firm-level insiders to institutional investors through private access to management (Brown, Call, Clement, and Sharp, 2017). Bushee, Jung, and Miller 2017 find that institutional investors who have access to firm-level insiders privately make more informed trading decisions. Utilizing illegal insider trading cases filed by the SEC and the DOJ, Ahern 2017 finds that information transmits locally via clusters of insiders with close social relationships and similar backgrounds. The findings are also supported by the theoretical argument that valuable information remains local, despite social networks being broad (Stein 2008).

Ex ante, whether the changes in the insider abnormal returns suggest that private, material information flows from firm level insiders to institutional investor cliques remains an archival question. However, my research design suggests that the public signaling channel is insufficient to explain the totality of my results. I analyze the insider behavior using staggered difference-in-difference designs with firm and year fixed effects which controls for systematic information environment changes at the firm level and a wide scope of time-varying covariates correlated with the firm's fundamentals.

My results are consistent with the information dissemination channel. Insider transactions in larger cliques exhibit lower abnormal trading profits, higher level of trading frequency, and larger amount of trade size, suggesting information dissemination is increasing in clique size. I indirectly analyze the magnitude of the public signaling channel through conditioning the analysis on whether the abnormal returns from an insider's trades change after plausible exogenous changes in the institutional investor clique sizes. The public signaling hypothesis would not predict an association between abnormal returns for firm-level insider transactions and clique size. Clique size changes are not likely to be correlated with any other changes in the information environment of the firm and firm fundamentals. Clique size changes will bring shocks to the firm-level insiders' information dissemination channels, while firm-level insiders are not likely able to predict changes in the clique sizes since they do not have access to proprietary information regarding potential holding changes for all clique members in the institutional investor clique ex ante. The information dissemination hypothesis predicts a negative association between the abnormal returns of firm-level insider purchases and clique size since insiders' private information disseminates faster in a larger clique.

Next, I utilize variation in clique size to proxy for the information dissemination rate and empirically test the relation between the value of information and the information dissemination rate. The information dissemination rate is positively associated with clique size (Garabedian and Dodd 1962). Using simulation results, Qian, Yagan, Yang, Zhang, and Xing (2013) find that information is much easier to propagate and disseminates much faster in larger cliques.

Theoretically, faster disseminating information can be more or less valuable. Prior research provides the sum of three terms for the value of information dissemination given the information dissemination rate (Hirshleifer et al. 1994; Holden and Subrahmanyam 2002; Han and Yang 2013; Manela 2014).[4] For example, faster dissemination allows for a faster realization of trading profits that are less prone to noise. Private information may be more quickly reflected in price, allowing for more predictable profits. However, all informed agents may trade more aggressively in stocks with more efficiently disseminated 'private' information, thus reducing the equilibrium value of information. Whether corporate insiders would benefit financially from the information dissemination depends on whether the relation between the value of information and information dissemination rate is monotonic (Han and Yang 2013) or hump-shaped (Manela 2014).

The results suggest that clique size is positively related to the information dissemination effects, suggesting the relation between the value of information and information dissemination rate is monotonic. In this setting, the informativeness of insider transactions is negatively associated with information dissemination. The effects for both purchases and sales are statistically significant and economically salient. One set of results suggest that 1 standard deviation increase in the clique size decreases the abnormal return for opportunistic insiders by 9.54 basis points.

This research complements the economic sociology literature on network externalities and provides a novel identification strategy that emphasizes the potential information conduits of information exchange. Network externalities are difficult to quantify (Glaeser, Laibson, and Sacerdote 2002). Prior research examines different forms of externality that involve one dyadic tie creating a spillover to other ties. The tests for clique size changes suggest information disseminates

[4] Manela 2014 provides a detailed description for these three terms that impact the relation between the value of information and the transmission rate.

within institutional investor cliques. Institutional investors receive proprietary information from companies they invested in, potentially exchange such proprietary information with other institutional investors for collaborative efforts while creating a spillover effect to members outside the network's direct social ties but within the institutional investor cliques. This research identifies clique-based networks as an alternative information dissemination channel among insiders.

This study answer calls from academia and regulatory bodies. Hirshleifer (2020) argues in the American Finance Association Presidential Address that social finance, an emerging field of inquiry, requires disentangling "the effects on investment choices of investor personality traits, the position of an investor in the social network, and overall network connectivity" (Hirshleifer 2020). A commonality in one dimension of social ties within the social network also creates biased information dissemination since participants in the social network have tendencies to interact with those who are similar (Cujean 2020; Han, Hirshleifer, and Walden 2019a). This paper argues that insiders may share information when they are exogenously positioned within a clique, releasing the assumption of commonality in any particular dimension. Since the insiders are not likely to have input for the formation of institutional investor cliques, institutional investor cliques capture the information dissemination effect without relying on the assumption that insiders share similar backgrounds in any specific dimension. This approach provides quasi-random selection for the network members that are biased against the homophily effect.

The clique-based information channel may help guide policy that better identifies potential insider trading activities. A key technological initiative of the Market Abuse Unit (MAU) of the SEC's Division of Enforcement's Analysis and Detection Center (A&D center) is ARTEMIS, the Advanced Relational Trading Enforcement Metrics Investigation System. Utilizing a "trader-based" approach, the MAU focuses on "the analysis of suspicious trading patterns and relationships among multiple traders" (Schapiro 2012), "identify insider trading by connecting patterns of trading to sources of material nonpublic information" (Friestad 2016) and identify patterns in multiple securities among traders who seem coordinating or have shared sources of private material information. This research provides novel evidence that private material information disseminates through institutional investor cliques. To the extent of my knowledge, no other research paper has studied such information dissemination channels in a systematic manner. Ahern (2017) finds that the prosecution of illegal insider trades focuses on homophily in one dimension (family, friends, or business associates), suggesting regulatory enforcement agencies focus on related party transactions. This paper argues that insiders may disseminate private material information when they are embedded in a social network involuntarily, releasing the assumption of commonality in any dimension. Investigators may be able to identify abnormal trading activities using a clique-based approach.

The results inform the timely debate regarding the reform of insider trading law. The House of Representatives passed the Insider Trading Prohibition Act in December 2019 ("IPTA"). The ITPA would not require the tippee to know whether the initial tipper received a personal benefit; while shifting the focus on whether the tippee knows that the information was received or communicated wrongfully.[5] Currently, United States v. Newman made it difficult for regulatory agencies to prosecute remote tippees since Newman's defense was that he was many links away from the original information source and the tipper is not likely to benefit from Newman. My results show that investors receive private material information from companies they invest in and disseminate such proprietary information within the cliques they reside in. Tippees who reside in

[5] IPTA explicitly states "It shall not be necessary that the person trading while aware of such information … knows the specific means by which the information was obtained or communicated, or whether any personal benefit was paid or promised by or to any person in the chain of communication, so long as the person trading while aware of such information or being aware, or recklessly disregarded that such information was wrongfully obtained, improperly used, or wrongfully communicated".

cliques are not regulated from disseminating or trading material private information under the current definition of illegal insider trading, suggesting that sophisticated investors who frequently trade on material private information are less likely to be convicted. Ahern (2017) also finds that information reaches sophisticated or well-capitalized traders after three links in the network, on average. Those traders are unlikely to be prosecuted.

CHAPTER TWO

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Literature Review

I develop a neoteric identification method that focuses on potential information dissemination through exogenously connected institutional investor networks. More specifically, I investigate 1) whether plausibly exogenous changes in network positions influence corporate insiders' firm-level information environment and information value reflected by the firm level insiders trading abnormal returns; 2) whether faster information dissemination is more or less valuable. This study contributes to the growing cross-disciplinary literature on information transfers across stakeholders; especially related to studies that examine the sources of information that lead to information dissemination and factors that influence the speed of information dissemination (Mehta et al. 2021).

Firm-level insiders have access to material private information unavailable to outside investors and have incentives to leverage such information for personal gain (Cohen et al. 2012). They also have incentives to share private material information within the institutional investor cliques. Zhang (2021) documents that firm-level insiders desire and benefit from exchanging information with institutional investors. Insiders have discretionary control over the level and type of information to disclose based on their idiosyncratic preferences and whether providing the information is likely to foster mutually beneficial relationships with investors (Park and Soltes 2018). Soltes (2018) finds that insiders tend to fabricate their own interpretation of Reg FD, since *material information* was not explicitly defined.[6] Firm directors also have incentives to share sensitive information with institutional investors as well. Akbas, Mexchke, and Wintoki (2016)

[6] Refer to *17 C.F.R. § 243.101 (2018).*

find that financial institutions make more informed trades on companies with more connected board members. Fisman et al. (2012) comment that "board membership more broadly creates a context for a kind of reciprocal attraction and friendship among a fraternity of individuals." Institutional investors also have incentives to exchange information with firm-level insiders. Material, private information is often disseminated from firm-level insiders to institutional investors through private access to management (Brown, Call, Clement, and Sharp 2019).[7] Bushee et al. (2017) and Solomon and Soltes (2015) find that institutional investors execute more informed trades if they have proprietary access to firm-level insiders.

2.2 Hypothesis Development

While Crane et al. (2019) focus on the coordination effect of institutional investor cliques, I study the information dissemination effects of institutional investor cliques. Theoretically, the information dissemination rate correlates positively with clique size (Garabedian and Dodd 1962). Using simulation results, Qian, Yagan, Yang, Zhang, and Xing (2013) find that information is easier to propagate and disseminates faster through larger cliques. Information leakage inadvertently increases with the number of participants who can potentially access material private information. The probability of leaking a private message is proportional to the square of the number of informed agents (Steele 1989). As clique size increases, it is more difficult to prevent unintended dissemination of material private information. The increase in the number of informed agents leads the stock price to respond to new information faster (Holden and Subrahmanyam 1992; Foster and Viswanathan 1993). Stock prices adjust faster for firms with more informed investors

[7] Survey evidence from hundreds of investor relations officers finds around 70% of companies offer private channels to communicate with offline access to senior executives. Prior studies also suggest meetings between institutional investors and managers offer relevant information based on how managers engage with investors through their voices and gestures. For example, visual perceptions of executives influence firm valuation (Blankespoor, Hendricks, and Miller, 2017), and vocal cues provide incremental information about firm fundamentals (Mayew and Venkatachalam, 2012).

(Brennan, Jegadeesh, and Swaminathan 1993; Badrinath, Kale and Noe 1995). Communications among insiders and institutional investors also favor "mosaic" information gathering by sophisticated minds.[8] When pieces of immaterial information are assembled into a holistic view of a firm, material information can be revealed. Sophisticated institutional investors can spend resources to piece together both firm-specific information and non-firm-specific information while even potentially (physically) tracking other institutional investors as well as corporate insiders.[9]

However, it is not certain that corporate insiders will disseminate private information to institutional investors. Institutional investors may not utilize insider information in trackable manner (Griffin et al., 2012). They may also not be willing to exchange such information outside their most trusted social network. Utilizing illegal trades data, Ahern (2017) finds that information disseminates regionally via clusters of insiders with homogeneous backgrounds and close social ties. The findings are also supported by the theoretical argument that valuable information remains local, despite social networks being broad (Stein 2008). Selective disclosure was prohibited by Regulation Fair Disclosure (17 C.F.R. pts. 240, 243, 249). Reg FD may be effective in deterring selective disclosure of material private information, since empirically Shao, Stoumbos, and Zhang (2021) document that earnings announcements returns have higher explanatory power on annual stock returns after 2003. Reg FD started deterring information spillover around 2004 (Kirk and Piao 2021). Corporate counsels have policies and procedures to prevent private information dissemination (Dai, Fu, Kang, and Lee 2016; Bird, Borochin, and Knopf 2015).

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[8] "Financial analysts are free to act on this collection, or mosaic, of information without risking violation" (CFA Institute Ethic Standard II(A) Material Nonpublic Information). www.cfainstitute.org/en/ethics-standards/codes/standards-of-practice-guidance/standards-of-practice-II-A#mosaic (accessed 6/4/2022).

[9] On December 3, 2012, John Carney from CNBC reported on "a fund manager who was allegedly paying off people to discover who was coming in and out of Teterboro Airport, the small New Jersey airport catering to many New York area private corporate jets," see www.cnbc.com/id/100272132 (accessed 6/4/2022). On October 20, 2011, Reuters' Jim Finkle reported that publicly traded companies directors are spied by malicious software installed on the Nasdaq's IT system by hackers. www.reuters.com/article/2011/10/20/us-nasdaq-hacking-idUSTRE79J84T20111020 (accessed 6/4/2022).

More importantly, insider transactions provide indicative signals to the market ("public signaling"). Disclosures of insider purchases on SEC Form 4 trigger positive market reactions and economically significant belief revisions about the firm (Veenman 2012; Brochet 2010). Insider purchases and sales by corporate executives reflect insiders' public signaling about their belief in proprietary information associated with potential stock returns (e.g., Jaffe 1974; Finnerty 1976; Seyhun 1986, 1998) and prospective cash flows (Piotroski and Roulstone 2005; Roulstone 2008). As a result, institutional investors and other market participants may mimic insider transactions, leading to a faster realization of insider abnormal returns.

By conditioning the analysis on whether the abnormal returns from an insider's trades change after exogenous changes in the institutional investor clique sizes, I offer evidence that the public signaling channel alone is not sufficient to explain the changes in the abnormal returns. Despite having low impact to the public signaling channel, changes in institutional investor clique sizes disrupt the information dissemination channels from firm-level insiders to institutional investor clique members while presenting low correlation with any changes in firm-level information environment or firm fundamentals. Firm-level insiders also have low predictive power to changes in the clique sizes since they do not have access to proprietary information regarding potential holding changes for all clique members ex ante. Private, material information can reach out to more clique members from firm-level insiders as clique size increases. If firm level insiders execute their trades based on material, private information, their trading profits would decrease if the clique sizes increase dramatically and vice versa. Prior literature classifies those insiders with such tendencies as "opportunistic insiders" (Cohen et al. 2012; Ali and Hirshleifer 2017). Compared to non-opportunistic insiders, opportunistic insiders are more likely to leverage private material information and bypass corporate governance mechanisms for personal gains. Therefore, opportunistic insider transactions offer ex ante directional predictions of insider purchases and sales. Consistent with the prior literature, I classify opportunistic insiders through the profitability of insiders' past-quarterly earnings announcements (QEA) trades (Ali and Hirshleifer 2017). My primary hypothesis, stated in null form is:

H1: Private, material information does not disseminate through institutional investor cliques.

Theoretical results provide the sum of three terms for the value of information provided the transmission rate (Hirshleifer et al., 1994, Han and Yang 2013, Holden and Subrahmanyam 2002, Manela 2014). The first term is positive and related to the uninformed agents' growing ability to precisely price the information over time. The second term is positive and related to the informed agents' growing ability to precisely price the information relative to the uninformed agents' over time. The third term is negative and related to the degree of information dissemination to the uninformed agents. The relative strength of each term varies based on the parameters of the model. Prior research is inconclusive on whether the relationship between the value of information and information dissemination rate is monotonic (Han and Yang 2013) or hump-shaped (Manela 2014).

Studying clique size provides a laboratory setting to test the relationship between the value of information and information dissemination rates for several reasons. First, clique size is a proxy for the information dissemination rate that offers directional predictions ex ante. This is directly related to the third term for the value of information. Not only does theoretical evidence suggest that clique size proxies for the information dissemination rate, but the interconnectedness of the clique also implies that members within the clique can acquire disseminated private material information at a very low cost (Marcoux and Lusseau 2013). Prior studies tend to use media exposure proxy for the information transmission rate (Tetlock 2007, Manela 2011). This measure can observe information transmission rate ex-post, while clique size offers directional predictions of information transmission ex-ante.

Second, through classifying insiders as opportunistic and non-opportunistic, I identify a group of insiders who possess private material information and are more willing to bypass corporate governance procedures for personal gains. Prior literature suggests corporate governance restricts the profitability of insider sales (Billings and Cedergren 2015; Dai, Fu, Kang, and Lee 2016). This implies that opportunistic insider purchases and sales offer directional predictions ex-ante.[10] Prior literature utilize positive events, such as drug approval, to study value of information. My study intends to offers prospective on the information dissemination process for both positive and negative material information. Third, extensive panel data across industries and years ensures the study incorporates a variety of material information. The variation in information type and interpretability is important for the first two terms for the value of information since the complexity and materiality of the information would influence the clique members' precision about the value of the information. By focusing on the information dissemination effects of a specific type of material information, the value of information could be biased against or towards the first two terms. For example, if the private material information is related to the missing analyst's forecast, the negative impact of the private information is relatively easy to understand and, therefore, offers high precision about returns. If the material information is related to the results of drug approval

[10] Note, I am not arguing that non-opportunistic insider purchases and sales do not have informational content. I am arguing that opportunistic insider purchases and sales offer directional predictions, while non-opportunistic insider purchases and sales do not offer directional predictions ex-ante.

or adoption of new technology, it requires a level of expertise and creates a learning curve to consume and, therefore, offers uninformed agents lower precision about returns.[11]

Utilizing clique size variance, variation in types of private, material information, and different types of insider transactions, this study examines the relationship between information dissemination rate and the value of information while controlling for the changes in the firm level information environment and the institutional information environment. Since the relative strength of each term for the value of information is inconclusive, the above discussion motivates my second hypothesis, stated in null form:

H2: Changes in clique size are not associated with insider trading profits and trading patterns.

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[11] For example, the approval of aducanumab marks the first time in 17 years that a drug treat neurodegenerative disease approved by FDA, while a number of experts claim that the drug has not been shown effective. See https://www.the-scientist.com/news-opinion/biogen-s-alzheimer-s-drug-gets-fda-approval-mixed-reviews-68851

CHAPTER THREE

RESEARCH DESIGN

3.1 Identify Information Dissemination in a Network

Although some forms of information dissemination within networks are directly observed (Di Maggio et al., 2019; Li, Wong, and Yu 2020), most archival studies test the information channels ex post because of the difficulty of identify the theorical prediction to test the information dissemination process ex ante. I proxy for the incentive and propensity of information dissemination within the institutional investors' network, utilizing the concept of complete subgraphs (cliques). A clique is an inter-connected subgraph within a social network. To pinpoint these subgraphs in the social network of institutions, I consider institutions are connected through mutual quarterly holdings. A connection is established if both investors owned 5% or more in one or more common firm(s) in the previous quarter. How connection is defined suggests that sharing common holdings in one or more firm(s) increase(s) the potential interactions between institutional investors and increases the probability for insiders of the firms within the holdings network to exchange and disseminate information. The construction is supported by survey evidence. Shiller and Pound (1989) find that the discussions among investors are the most important driver of investment decisions. Abramova, Core, and Sutherland 2020 find that monitoring by institutions causes managers to increase the number of disclosures which may have limited effects on information quality.

The Louvain algorithm clusters investors that are more likely to exchange information within subgroups and is widely used for clique measurement (Crane et al., 2019; Qian et al., 2013). The method clusters investors so that the proportion of investor connections outside of the clique is highly correlated to the proportion of investor connections in the clique. The algorithm dictates the formation of cliques. Institutional investors are either assigned to one specific clique or no clique. The Louvain method is suitable for this study for several reasons. First, the Louvain method is popular due to its scalability and stable performance in various sizes of social networks. The number of institutional investors changes overtime, suggesting the network sizes change over the years (Fichtner 2020). By checking the interest of moving to neighbor's communities, the Louvain method benefits from the variability and the sparsity of the network. The Maximum Clique Method may perform well in sparse graph, but is not suitable for dense graph since it makes a large matrix. Second, the Louvain method effectively mitigates the problem of the resolution limit. Limit of resolution is an important drawback of Modularity, meaning the partitions of maximal modularity are biased toward a particular scale or given size. A classic example would be the ring clique. The Louvain method can identify each clique in its community at the first level.

More importantly, the Louvain algorithm allows me to study the vertex partition of the social network. The Maximum Clique Method or other clique clustering methods are more suitable to study the interaction between different types of social networks (Evans 2010). For example, friendships, family relationships, and work collaborations may all be formed through a common hobby or going to the same school. However, the research is to investigate the relationship between the institutional investor clique and the information dissemination effect within the cliques. In this study, the algorithm that produces stable results for vertex partition is the most fitted for the study. Due to the wide acceptance and stable performance, I choose the Louvain method for clustering.

Each quarter, I build a square matrix representing institution-to-institution relationships. The off-diagonal elements assign a dummy variable of one if these two off-diagonal institutions have a holding larger or equal to 5% in common in at least one firm. I estimate subgraph from this network of ownership holdings, utilizing the Louvain algorithm (Blondel et al. 2008). Each cross-section data (based on the reported holding per quarter) is generated independently since the algorithm is static. Examples of cliques (and non-cliques) are provided in Figure 1. In Figure 1, institutions 1, 2, 3, 4, and 5 belong to the same clique. This clique is the largest in Figure 1, with the most interconnected institutions. Institutions 9, 10, 11, and 12 belong to the same clique, while institutions 6, 7, and 8 belong to the same clique. Note, institutions 13-16 do not belong to a clique since they are not all interconnected with one another. Intuitively, information may disseminate more quickly from a clique member to any other member resides in the clique. As to the social structure formed by institutions 13, 14, 15, and 16, information must transmit through institution 13. Information dissemination, therefore, is more difficult within this subgraph of the network (Crane et al., 2019). Firm-level insiders are corporate executives, directors and beneficiary owners at the firm level. For example, for Clique composed of institutions 6, 7, and 8, firm level insiders include all the firm level insiders who file Form 4 in Firm Q, R, and S.

After classifying the institutional investors that reside in each individual clique in each quarter, I construct a firm-level measure of exogenous increase or decrease in clique size. First, I calculate the clique size measure at the firm level for each year utilizing the Louvain method, ensuring every institution is assigned to no clique or only one specific clique in a given year. A given firm's clique size is calculated below:

$$Weighted\ Clique\ Size_{j,t} \ = \ \sum_i^n \ (\lambda_{i,t} * \sum_i^N \mathbb{1}(Clique\ institution_{i,t})) \tag{1}$$

where $\lambda_{i,t}$ is institution i's percent holdings in firm j at time t, and $\mathbb{1}(Clique\ institution_{i,t})$ is an indicator variable equals to one if the institution i belongs to a clique at time t. The sum of

$\mathbb{1}(Clique\ institution_{i,t})$ represents the total number of institutions in the clique to that institution i belongs.[12] The sum of $\lambda_{i,t} * \sum_{i}^{N} \mathbb{1}(Clique\ institution_{i,t})$ represents the sum of institution *i*'s institutional ownership ratio in firm j multiplies the total number of institutions in the clique that institution i belongs. This measure accounts for the clique size proportioned by the institutional ownership, proxying for the information dissemination rate. In the robustness section, I also provide alternative clique size measures that are free from the influence of institutional ownership.

3.2 Data and Hypotheses Tests

I construct institutional ownership data from the Thomson Reuters 13F database. Using calendar quarter-end holdings data, I first identify duplicated cases where the manager reports multiple positions for a given report date for a single stock, replacing the holdings data from the most recent filling date. I also fill the missing data by carry holdings forward for one period (Griffin and Xu 2009). I utilize the Thomson Reuters 13F database to merge with CRSP and Compustat – Capital IQ to construct the clique measurements. At the institutional investor level, I identify an average of 12.41 institutional investor cliques each quarter from the first quarter of 1986 to the last quarter of 2013.[13] The median number of clique members is 44.

Next, I merge the data with insider trading data obtained from Thomson Reuters Insider Trading Database. I follow Ali and Hirshleifer 2017 to identify opportunistic insiders. Ali and Hirshleifer 2017 use pre-quarterly earnings announcement (QEA) trades to identify *Opportunistic Insiders*. A pre-QEA trade is a trade that occurs during the 21 trading days before the QEA, excluding the last two days before the QEA. The method disentangles the performance of the

[12] Per the Louvain Method, one institution can only belong to a maximum of one clique.

[13] WRDS documents serious problems with the data starting in 2013 caused by stale and omitted 13F filings (Lewellen and Lewellen 2022).

trades of *Non-Opportunistic Insiders* with *Opportunistic Insiders* during the same year and at the same firm to mitigate the possibility that the results are determined by firm characteristics not associated with insider opportunism.

3.3 Descriptive Statistics

Table 1 presents trade-level summary statistics. *Weighted Clique Size* has a mean value of 38.11 for the opportunistic insider purchases subsample, representing that, for a given firm on average, there are 38.11 institutional investors in the clique during the year, adjusted for the institutional ownership. *Weighted Clique Size* has a mean value of 43.78 for the opportunistic insider sales subsample, representing that, for a given firm on average, there are 43.78 institutional investors in the clique during the year, adjusted for the institutional ownership. A continuous variable of the firm level measure for the number of institutional investors in the clique during the year, adjusted for the institutional ownership. The inter-quartile range is 11.448 - 57.405 for the opportunistic insider purchases subsample and is 21.182 - 62.053 for the opportunistic insider sales subsample, suggesting substantial variation. The descriptive statistics for the variable *Weighted Clique Size* is consistent with those for the variable *Clique Size*, suggesting institutional holdings are not driving the variation in *Weighted Clique Size*. *Weighted Clique Size* may be correlated with ownership proxies. Institutional ownership concentration (IO Concentration) is negatively related to *Weighted Clique Size*, suggesting a possible substitution effect. I present the evidence of this substitution in Figure 3. I draw the *Average Institutional Ownership Concentration* (Hartzell and Starks, 2003) each year. Note, top institutional owners experience a drop in the average holding size for individual firms across the years. *Weighted Clique Size* has risen over the same period. Prior research finds a positive association between the proportion of institutional ownership and the extent of voluntary disclosure (Bushee and Noe 2000). If members of this clique are exchanging information, such an association could have an alternative explanation: an increase in clique size facilitates information dissemination within the clique that reduces the demand for voluntary disclosure.

3.4 Empirical Tests of Hypotheses

I analyze the abnormal returns of inside trades based on the exogenous changes in clique size as well as *Weighted Clique Size.* I first compute the equal-weighted average abnormal annual return from inside trades as estimated in Jagolinzer et al. (2011). They estimate abnormal profits per trade as the α (-α for sales) from a four-factor Fama-French (1993) and Carhart (1997) model estimated over the 180 days following the transaction, which we represent in the following equation:

$$(R_{j,t} - R_{f,t}) = \alpha + \beta 2\ (Rmkt_t - R_{f,t}) + \beta 3\ SMB_t + \beta 4\ HML_t + \beta 5\ UMD_t + e_t \qquad (2)$$

where on a given day t, $R_{j,t}$ is the daily return to firm *j*'s equity, $R_{f,t}$ is the daily risk-free interest rate, $Rmkt_t$ is the daily CRSP value-weighted market return, SMB_t, HML_t, and UMD_t are the daily size, book-to-market, and momentum factors (Fama and French 1993, Carhart 1997), and α (-α) is $Insider\ Abnormal\ Returns_{i,t}$, the average daily risk-adjusted return to a net purchase (sale) during the 180 days following the transaction.

The sample contains 128,779 purchases and 357,342 sales. I follow Ali and Hirshleifer 2017 for the classification of opportunistic trades and find that 29,931 of those purchases are opportunistic purchases, while 68,265 of those sales are opportunistic sales. *Insider Abnormal Returns* has a mean value of 0.052 for purchases and 0.057 for sales. On the purchase side, the mean value of abnormal insider returns for *the Opportunistic* dummy variable is 0.113 while the mean value of the insider abnormal returns for the *Non-Opportunistic* dummy variable is 0.037. On the sales side, the mean value of the insider abnormal returns for *the Opportunistic Insider Returns* is -0.042 while the mean value of the insider abnormal returns for the *Non-Opportunistic Insider Returns* is 0.077.[14] These coefficients represent daily basis points. There are 9,425 unique firms and 49,707 unique Section 16 insiders in the sample. Section 16 insiders make around 240 purchase trades per firm-quarter, with 142 of these being opportunistic, and make around 382 sales trades per firm-quarter, with 30 of these being opportunistic.

Figure 4A and Figure 4B plot the average *Insider Abnormal Returns* across ten different clique sizes for both opportunistic insiders and non-opportunistic insiders to provide a visual representation of the relation between average abnormal returns and the clique size. Intuitively, the trend suggests that greater clique size, a proxy for higher information transmission rate, is correlated with a lower value of informed trades. I observe that the *Insider Abnormal Returns* for these two groups of insiders decrease as the *Weighted Clique Size* increases. On the purchase side (Figure 4A), both non-opportunistic and opportunistic insiders earn larger abnormal returns in smaller cliques, while non-opportunistic insiders consistently earn lower profits compared to opportunistic traders. The decrease in profit for both types of insiders suggest the effect of information dissemination is probably stronger for insiders residing in larger cliques for both non-opportunistic insiders and opportunistic insiders. Prior research also suggests that corporate governance tends to restrict the profitability of insider sales but not that of insider purchases (Dai, Fu, Kang, and Lee 2016). On the sales side (Figure 4B), insiders who earn negative abnormal returns are more likely to be opportunistic insiders, while insiders who earn positive abnormal returns are more likely to be non-opportunistic insiders. The average insider abnormal return

[14] Consistent with prior literature, non-opportunistic sales are assumed to be generally liquidity driven and have lower returns.

increases for an opportunistic insider as the average weighted clique size increases, suggesting the information dissemination effect is stronger in larger cliques. The insider sales transactions also suggest that both corporate governance and information dissemination influence insider abnormal returns. The non-opportunistic insiders do not seem to earn much abnormal returns potentially due to the corporate governance effects on the insider sales transactions.

To test hypothesis 1, I use a difference-in-difference (DID) model to test whether there is any information dissemination effect when firm joins a clique. I first use *Weighted Clique Size* to examine whether sudden changes in clique sizes influence corporate insiders' firm-level information environment. *Weighted Clique Size* is defined as the number of institutions that belong to the clique on a quarterly basis. I estimate the following OLS regressions only on opportunistic trades with firm and year fixed effects when firms join cliques:

$$\begin{aligned} &\textit{Insider Abnormal Returns}_{i,t} = \beta 1\ \textit{Weighted Clique Size} + \beta 2\ \textit{Post Join} + \\ &\beta 3\ \textit{Weighted Clique Size} * \textit{Post Join} + \textit{Firm FE} + \textit{Year FE} + e_{i,t} \end{aligned} \tag{3}$$

Where *Insider Abnormal Returns* is the average daily risk-adjusted return to a net purchase (sale) by executive *i* during the 180 days following the transaction on day t (α (-α) on from equation (1)). *Post Join* dummy is a dummy variable equals 1 for firms that join a clique and equal to 0 for firms that do not join a clique. The sample consists of observations three years prior to the date when a firm exits a clique and three years after the date when a firm exits a clique. *Weighted clique size* may conflate ownership level and clique size. To ensure the results are not driven by the institutional investors' ownership level, I construct two alternative measures representing *Weighted Clique Size*: *Changes in Clique Size* and *Changes in Clique Size Scaled by Prior Clique* for robustness tests. *Changes in Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the number of institutional investors in the clique in the prior year. *Changes in Clique Size Scaled by Prior Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the number of institutional investors in the clique in the prior year divided by the number of institutional investors in the clique in the prior year.

I also use a difference-in-difference (DID) model to test whether there is any information dissemination effect when firm exits a clique. I estimate the following OLS regressions only on opportunistic trades with firm and year fixed effects when firms exit cliques:

$$\begin{aligned}&\textit{Insider Abnormal Returns}_{i,t} = \beta 1\ \textit{Weighted Clique Size} + \beta 2\ \textit{Post Exit} + \\ &\beta 3\ \textit{Weighted Clique Size} * \textit{Post Exit} + \textit{Firm FE} + \textit{Year FE} + e_{i,t} \qquad (4)\end{aligned}$$

Where *Insider Abnormal Returns* is the average daily risk-adjusted return to a net purchase (sale) by executive *i* during the 180 days following the transaction on day t (α (-α) on from equation (1)). *Post Exit* dummy is a dummy variable equals 1 for firms that exit a clique and equals 0 for firms that do not exit a clique. The sample consists of observations three years prior to the date when a firm exits a clique and three years after the date when a firm exits a clique. *Weighted clique size* may conflate ownership level and clique size. To ensure the results are not driven by the institutional investors' ownership level, I construct two alternative measures representing *Weighted Clique Size*: *Changes in Clique Size* and *Changes in Clique Size Scaled by Prior Clique* for robustness tests. *Changes in Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the number of institutional investors in the clique in the prior year. *Changes in Clique Size Scaled by Prior Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the number of institutional investors in the clique in the prior year divided by the number of institutional investors in the clique in the prior year.

Additionally, I use a dynamic difference-in-difference (DID) model to ensure that the effect is immediate for joining the clique. Following Huang and Wang (2021), I estimate the following OLS regressions only on opportunistic trades with firm and year fixed effects when firms join cliques:

$$\text{Insider Abnormal Returns} = \beta 1\ \textit{Join Clique} * \textit{Year -2} + \beta 2\ \textit{Join Clique} * \textit{Year -1}$$
$$+ \beta 3\ \textit{Join Clique} * \textit{Year 1} + \beta 4\ \textit{Join Clique} * \textit{Year 2} + \text{Firm FE} + \text{Year FE} + e_{i,t} \qquad (5)$$

where *Join Clique* equals 1 if the firm joins a clique during the sample period, and 0 otherwise. Dummies Year -2, Year -1, Year 1, and Year 2+ are indicator variables set to 1 if the firm-year is two years before, one year before, one year after, and two or more years after a firm joins a clique, respectively (with Year 0 being the benchmark year). Since the model includes the firm and year fixed effects, it does not include the main effects of Join Clique and dummies Year -2, Year -1, Year 1, and Year 2. The yearly effect of Join Clique on Insider Abnormal Returns, relative to firms that do not join the clique, is captured by the interaction terms of Join Clique and dummies Year -2, Year -1, Year 1, and Year 2+, respectively.

I also use a dynamic difference-in-difference (DID) model to ensure that the effect is immediate for exiting the clique. I estimate the following OLS regressions only on opportunistic trades with firm and year fixed effects when firms exit cliques:

$$\text{Insider Abnormal Returns} = \beta 1\ \textit{Exit Clique} * \textit{Year -2} + \beta 2\ \textit{Exit Clique} * \textit{Year -1} + \beta 3\ \textit{Exit Clique} * \textit{Year 1} + \beta 4\ \textit{Exit Clique} * \textit{Year 2} + \text{Firm FE} + \text{Year FE} + e_{i,t} \tag{6}$$

where *Exit Clique* equals 1 if the firm exits a clique during the sample period, and 0 otherwise. Dummies Year -2, Year -1, Year 1, and Year 2 are indicator variables set to 1 if the firm-year is two or more years before, one year before, one year after, and two years after a firm joins a clique, respectively (with Year 0 being the benchmark year). Since the model includes the firm and year fixed effects, it does not include the main effects of Exit Clique and dummies Year -2, Year -1, Year 1, and Year 2. The yearly effect of Exit Clique on Insider Abnormal Returns, relative to firms that do not exit the clique, is captured by the interaction terms of Exit Clique and dummies Year -2, Year -1, Year 1, and Year 2, respectively.

To test hypothesis 2, I first use *Weighted Clique Size* to examine whether changes in clique sizes influence corporate insiders' firm-level information environment and insider trading patterns. *Weighted Clique Size* is defined as the number of institutions that belong to the clique on a quarterly basis. This infra-firm analysis controls the potential possibility to trade base on private information since the design includes time-invariant firm-level characteristics (for example, the firm's institutional holdings and control environments). I incorporate firm – year effects to control for variations in social norms or regulatory changes of insider trading laws. I estimate the following OLS regressions only on opportunistic trades with firm – year fixed effects:

$$\textit{Dependent Variables}_{i,t} = \beta 1\ \textit{Weighted Clique Size} + \textit{Firm} - \textit{Year FE} + e_{i,t} \tag{7}$$

Where *Dependent Variables* are *Insider Abnormal Returns, Number of Trades*, and *Trade Size*. *Insider Abnormal Returns* is the average daily risk-adjusted return to a net purchase (sale) by executive *i* during the 180 days following the transaction on day t (α (-α) on from equation (1)). *Number of Trades* is a continuous variable of the firm level measure for the natural logarithm of the number of inside trades plus 1 per quarter. *Trade Size* is the natural logarithm of the number of shares traded plus 1 aggregated on the date insider transaction occurred. There are firm – year indicators. The firm – year fixed effects subsume all variables that are measured at annual frequency. The design choice is important since it controls for firm characteristics that may be associated with institutional investor's decision to invest, leading to clique size changes.[15]

Then, I examine whether the *Insider Abnormal Returns* and insider trading patterns are linearly associated with the *Weighted Clique Size Centered*, proxying the relationship between the value of information and the information dissemination rate. I incorporate firm – year effects to control for variations in social norms or regulatory changes of insider trading laws. I estimate the following OLS regressions on opportunistic insiders with firm – year fixed effects:

$$\textit{Dependent Variables}_{i,t} = \beta 1\ \textit{Weighted Clique Size Centered} + \beta 2\ \textit{Weighted Clique Size Centered} * \textit{Weighted Clique Size Centered} + \textit{Firm} - \textit{Year FE} + e_{i,t} \quad (8)$$

Where *Dependent Variables* are *Insider Abnormal Returns, Number of Trades*, and *Trade Size*. *Insider Abnormal Returns* is the average daily risk-adjusted return to a net purchase (sale) by executive *i* during the 180 days following the transaction on day t (α (-α) on from equation (1)). *Number of Trades* is a continuous variable of the firm level measure for the natural logarithm of

[15] Refer to Arif et al. (2020) and Blackburne et al. (2020) for similar design choices on fixed effects.

the number of inside trades plus 1 per quarter. *Trade Size* is the natural logarithm of the number of shares traded plus 1 aggregated on the date insider transaction occurred. *Weighted Clique Size Centered* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the average number of institutional investors in the clique for the whole sample. I center the variable *Weighted Clique Size*, since *Weighted Clique Size* and *Weighted Clique Size * Weighted Clique Size* are highly corrected (correlation 0.99). Once the variable is centered, the correlation between *Weighted Clique Size Centered* and *Weighted Clique Size Centered * Weighted Clique Size Centered* is 0.35.

The model also contains firm – year fixed effects since insider trades can vary systematically among different firms and throughout years (Arif, Kepler, Schroeder, and Taylor 2020; Blackburne, Kepler, Quinn and Taylor 2020; Davidson and Pirinsky 2022). Controlling for time series shifts in factors correlated with the changes in the clique size over time, the fixed effects design takes within firm – year variation in insider trading characteristics into consideration. Even I cannot rule out correlated omitted variables; such variables have to vary within the firm and associated with the timing of insiders' trades, the firm level stock returns, and the change in clique size over time, which is not directly associated with the sample observations and occurs at 29,487 different points in time across the sample firms.

CHAPTER FOUR

RESULTS

4.1 Baseline Results of Hypothesis 1

Table 3 Panel A provides an analysis of equation (3) for the abnormal returns. The dependent variables are *Insider Abnormal Returns*, as defined in equation (2). The two columns are OLS regressions of *Insider Abnormal Returns* with firm and year fixed effects. For column 1 and 2, the primary variable of interest, *Weighted Clique Size x Post Join*, is negative and significant on the sale side, suggesting that additional information dissemination channels are created after a firm join a clique, and such information dissemination process reduces abnormal insider returns. Note, the purchase side is not significant due to a limited number of observations. I analyze the regression without cluster by standard errors. The purchase side is negative and statistically significant. This econometric practice is acceptable. Recently literature shows that the conventional approach to correct for correlated errors may be biased downwards when the number of clusters is small (generally <50) (Rokicki, Cohen, Fink, Salomon, Landrum 2018; Cameron and Miller 2015; Donald and Lang 2007; McCaffrey and Bell 2006). Overall, the results suggest that additional information dissemination channels are created after a firm joins a clique, and such information dissemination process reduces abnormal insider returns.

To ensure the robustness, Table 3 Panel B and Panel C provide an analysis of equation (3) for the abnormal returns utilizing two alternative measures representing *Weighted Clique Size*: *Changes in Clique Size* and *Changes in Clique Size Scaled by Prior Clique*. In Table 3 Panel B, *Changes in Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the number of institutional investors in the clique in the prior year. The two columns are OLS regressions of *Insider Abnormal Returns* with firm and year fixed effects. For column 1 and 2, the primary variable of interest, *Changes in Clique Size x Post Join*, is negative and significant on the sale side, suggesting that additional information dissemination channels are created after a firm join a clique, and such information dissemination process reduces abnormal insider returns. The results are consistent with the results in Table 3 Panel A.

In Table 3 Panel C, *Changes in Clique Size Scaled by Prior Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the number of institutional investors in the clique in the prior year divided by the number of institutional investors in the clique in the prior year. The two columns are OLS regressions of *Insider Abnormal Returns* with firm and year fixed effects. For column 1 and 2, the primary variable of interest, *Changes in Clique Size Scaled by Prior Clique Size x Post Join*, is negative and significant on the sale side, suggesting that additional information dissemination channels are created after a firm join a clique, and such information dissemination process reduces abnormal insider returns. The results are consistent with the results in Table 3 Panel A.

Table 4 Panel A provides analyses of equation (4) for the impact of exogenous changes in clique size on *Insider Abnormal Returns* when a firm exits a clique. The dependent variable *Insider Abnormal Returns* is defined in equation (2). The two columns are OLS regressions of *Insider Abnormal Returns* with firm and year fixed effects. For column 1 and 2, the primary variable of interest, *Weighted Clique Size x Post Exit*, is positive and significant on the both purchase and sale sides, suggesting that the established information dissemination channels are depleted after a firm exit a clique and such depletion process increases *Insider Abnormal Returns*. Note, once the firm exits a clique, the complete impact for the *Insider Abnormal Returns* (coefficients for the *Weighted Clique Size* and the *Weighted Clique Size x Post*

Exit) is positive for purchases (Column 1) and negative for sales (Column 2). This suggests that 1) opportunistic insiders seem to share way less private material information regarding their purchase decisions after their exit from the cliques leading those trades to earn positive abnormal returns; 2) opportunistic insiders seem to share less private material information related to their sales decisions after they exit the cliques. However, those sales trades earn negative abnormal returns overall. The findings are consistent with prior literature. On the Sales side, institutional investor cliques may corporate and perform corporate governance functions via exit (Crane et al., 2019). Overall, Table 4 Panel A offer direct and consistent evidence that information channels are diminished and information dissemination rate is lower when a firm exits a clique.

To ensure the robustness, Table 4 Panel B and Panel C provide an analysis of equation (4) for the abnormal returns utilizing two alternative measures representing *Weighted Clique Size*: *Changes in Clique Size* and *Changes in Clique Size Scaled by Prior Clique*. In Table 4 Panel B, *Changes in Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the number of institutional investors in the clique in the prior year. The two columns are OLS regressions of *Insider Abnormal Returns* with firm and year fixed effects. For column 1 and 2, the primary variable of interest, *Changes in Clique Size x Post Exit*, is positive and significant on the both purchase and sale sides, suggesting that the established information dissemination channels are depleted after a firm exit a clique and such depletion process increases *Insider Abnormal Returns*. The results are consistent with the results in Table 4 Panel A.

In Table 4 Panel C, *Changes in Clique Size Scaled by Prior Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the number of institutional investors in the clique in the prior year divided by the number of institutional investors in the clique in the prior year. The two columns are OLS regressions of *Insider Abnormal Returns* with firm and year fixed effects. For column 1 and 2, the primary variable of interest, *Changes in Clique Size Scaled by Prior Clique Size x Post Exit*, is positive and significant on both purchase and sale sides, suggesting that the established information dissemination channels are depleted after a firm exit a clique and such depletion process increases *Insider Abnormal Returns*. The results are consistent with the results in Table 4 Panel A.

To ensure the robustness of the results above, I also perform Dynamic DID regressions and provide the results on Table 5 and Table 6. Table 5 provides analyses of equation (5) for the impact of exogenous changes in clique size on *Insider Abnormal Returns* when a firm joins a clique. The dependent variable *Insider Abnormal Returns*, is defined in equation (2). In Panel A, the two columns are Dynamic DID regressions of *Insider Abnormal Returns* with firm and year fixed effects. For column 1 and 2, the primary variable of interest, *Join Clique * Year 1* and *Join Clique * Year* +2 are both negative and significant, suggesting that insiders receive lower level of insider abnormal returns after the firm joins a clique. Note, compared to the benchmark year (Year 0), some of the *variables Join Clique * Year -2* and *Join Clique * Year -1* are positive, suggesting that insiders receive higher level of insider abnormal returns prior to the firm joining a clique. The findings provide direct evidence that additional information channels are created after a firm joins a clique and insiders disseminate private material information through those information channels.

Table 6 provides analyses of equation (6) for the impact of exogenous changes in clique size on *Insider Abnormal Returns* when a firm exits a clique. The dependent variable *Insider Abnormal Returns*, is defined in equation (2). In Panel A, the two columns are Dynamic DID regressions of *Insider Abnormal Returns* with firm and year fixed effects. For column 1 and 2, the primary variable of interest, *Exit Clique * Year 1* and *Exit Clique * Year 2* are both positive and significant, suggesting that insiders receive higher level of insider abnormal returns after the firm exits a clique. The findings provide direct evidence that information channels are depleted after a firm exits a clique and insiders are not able to disseminate private material information through those depleted information channels.

Overall, the results from Table 3, 4, 5, and 6 show that, when joining a clique, insider transactions exhibit lower abnormal trading profits. When exiting a clique, insider transactions exhibit higher abnormal trading profits. The consistent results show that private, material information disseminate through institutional investor cliques.

4.2 Baseline Results of Hypothesis 2

To test hypothesis 2, I present the results in Table 7. Table 7 provides analyses of equation (7) for the relationship between changes in clique size and the insider trading profits and trading patterns. The results from Table 7 offer consistent and direct evidence that the changes in *Weighted Clique Size*, proxy for changes in information dissemination channels, significantly impact the abnormal profits on insiders' opportunist trading. The *Number of Trades* and *Trade Size* are positively associated with *Weighted Clique Size*, suggesting that insiders perceive themselves to be more informed when they are placed in a larger clique. The results also provide evidence that information disseminates within a network even if the network members are involuntarily connected through the network. The results are also economically significant. Using Column 1 as an example, 1 standard deviation increase in the *Weighted Clique Size* decreases the *Insider Abnormal Returns* for opportunistic insiders by 9.54 basis points. The results above suggest the *Insider Abnormal Returns* for both opportunistic insider purchases and opportunistic insider sales decrease as *Weighted Clique Size* increases, suggesting a greater level of information dissemination. This identification strategy suggests that the network members can connect while disregarding any specific type(s) of commonality (common schooling, same/similar organizations, or shared clubs) and provides evidence of within network information dissemination. Note, the results do not imply or preclude specific type(s) of commonality within the clique, it is simply not required. To ensure that the results are not driven by the variable of interest, I replace the variable of interest *Weighted Clique Size* with *Changes in Clique Size* and *Changes in Clique Size Scaled by Prior Clique Size*. The results are similar and economically significant. Using Table 9 Column (1) as an example, 1 standard deviation increase in the *Changes in Clique Size* decreases the *Insider Abnormal Returns* for opportunistic insiders by 8.51 basis points.

Table 8 Panel A provides analysis of equation (8) to test whether the relationship between the value of information and information dissemination rate is linear, utilizing high order polynomial regressions. The dependent variable *Insider Abnormal Returns*, is defined in equation (2). The dependent variable *Number of Trades* is a continuous variable of the firm level measure for the natural logarithm of the number of inside trades plus 1 per quarter. The dependent variable *Trade Size* is the natural logarithm of the number of shares traded plus 1 aggregated on the date the insider transaction occurred. *Weighted Clique Size Centered* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the average number of institutional investors in the clique for the whole sample. I center the variable *Weighted Clique Size*, since *Weighted Clique Size* and *Weighted Clique Size * Weighted Clique Size* are highly corrected (correlation 0.99). Once the variable is centered, the correlation between *Weighted Clique Size*

Centered and *Weighted Clique Size Centered * Weighted Clique Size Centered* is 0.35. In Panel A, the first two columns are OLS regressions of *Insider Abnormal Returns* with firm – year fixed effects. The second two columns are high order polynomial regressions of *Insider Abnormal Returns* with firm – year fixed effects. For column 1 and 2, the primary variable of interest, *Weighted Clique Size Centered*, is negative and significant, consistent with the original findings. For column 3 and 4, the primary variable of interest, *Weighted Clique Size Centered * Weighted Clique Size Centered*, is insignificant, suggesting that the relationship between the value of information and information dissemination rate is linear. In Panel B, the first two columns are OLS regressions of *Number of Trades* with firm – year fixed effects. The second two columns are high order polynomial regressions of *Number of Trades* with firm – year fixed effects. For column 1 and 2, the primary variable of interest, *Weighted Clique Size Centered*, is positive and significant, consistent with the original findings. For column 3 and 4, the primary variable of interest, *Weighted Clique Size Centered * Weighted Clique Size Centered*, is insignificant, suggesting that the relationship between the value of information and information dissemination rate is linear. In Panel C, the first two columns are OLS regressions of *Trade Size* with firm – year fixed effects. The second two columns are high order polynomial regressions of *Trade Size* with firm – year fixed effects. For column 1 and 2, the primary variable of interest, *Weighted Clique Size Centered*, is positive and significant, consistent with the original findings. For column 3, the primary variable of interest, *Weighted Clique Size Centered * Weighted Clique Size Centered*, is insignificant, suggesting that the relationship between the value of information and information dissemination rate is linear. For column 4, the primary variable of interest, *Weighted Clique Size Centered * Weighted Clique Size Centered*, is significant. However, the coefficient is very close to 0, suggesting that very limited evidence supports that the relationship between the value of information and information dissemination rate is not linear on the sales side. Overall, the results suggest that the relationship between the value of information and the information dissemination rate is linear.

4.3 Alternative Measures of Clique Sizes

Weighted clique size could conflate ownership level and clique size. To ensure the results are not driven by the institutional investors' ownership level, I construct three alternative measures representing *Weighted Clique Size*: *Changes in Clique Size* and *Changes in Clique Size Scaled by Prior Clique* for robustness tests. *Changes in Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the number of institutional investors in the clique in the prior year. *Changes in Clique Size Scaled by Prior Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the number of institutional investors in the clique in the prior year divided by the number of institutional investors in the clique in the prior year. This variable is constructed without scaling the institutional investors' ownership level. I utilize these alternative measures to replace *Weighted Clique Size* to replicate the tests in Table 7. I present the results in Table 9 and Table 10.

For Table 9, the primary variable of interest, the interaction term *Changes in Clique Size*, is negatively associated with the *Insider Abnormal Returns*, suggesting that a highly level of information dissemination as clique size increases. The *Number of Trades* and *Trade Size* are positively associated with *Changes in Clique Size*, suggesting that insiders perceive themselves to be more informed when they are placed in a larger clique.

For Table 10, the *Insider Abnormal Returns* are negatively associated with *Changes in Clique Size Scaled by Prior Clique Size*, suggesting that a highly level of information dissemination as clique size increases. The *Number of Trades* and *Trade Size* are positively associated with *Changes in Clique Size Scaled by Prior Clique Size*, suggesting that insiders perceive themselves to be more informed when they are placed in a larger clique.

CHAPTER FIVE

CONCLUSION

5.1 Conclusion

This research complements the economic sociology literature on network externalities and provides a novel identification strategy that focuses on the possible information conduits of information exchange. I analyze the relation between insider trading outcomes and insiders' information environment within the network. While most existing studies rely on one dimension of commonalities (personal ties, professional ties, and geographic proximity) to construct the social network, I document the formation of the institutional investor groups (cliques) that exogenously connect firm-level insiders within the social network. Institutional investors receive proprietary information from companies they invested in, potentially exchange such proprietary information with other institutional investors for collaborative efforts while creating a spillover effect to insiders outside the network's direct ties but within the institutional investor cliques. Using a Difference-in-Difference design on changes in clique sizes, I provide empirical evidence on the information dissemination channels within a network where its members are quasi-randomly selected. Fixed effects models also confirms that insider transactions in larger cliques have a lower level of trading profits, smaller trading size, and a higher number of trades, suggesting higher levels of information dissemination for larger cliques. I also study the value of information dissemination in the controlled setting where the information dissemination rate for firm-level opportunistic insiders, who possess material non-public information, varies based on the size of the institutional investor clique they reside. I provide empirical evidence that the relationship between the value of information and the information dissemination rate is monotonic, consistent with Han and Yang (2013).

This study answers calls from academia and regulatory bodies. This paper answers the calls in the 2020 AFA Presidential Address for a deeper understanding of "social transmission bias: systematic directional shift in signals induced by social transactions", by utilizing the variation in the clique size to proxy for the information dissemination rate as well as empirically testing the relationship between the value of information and the information dissemination rate. Homophily posts a pervasive identification challenge in the empirical social network literature. Since the insiders are not responsible for the formation of institutional investor cliques, this method provides quasi-random selection for the network members that lifted the commonalities (personal ties, professional ties, and geographic proximity) assumption in any one dimension. The clique-based information channel may also help guide policy that better identifies potential insider trading activities. This paper finds evidence that insiders may share information when they are exogenously positioned within a clique, releasing the assumption of commonality in any dimension. Investigators may be able to identify abnormal trading activities using a clique-based approach.

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APPENDIX A

VARIABLE DEFINITIONS

Variable	Definition and Data Source
Weighted clique size	A continuous variable of the firm level measure for the number of institutional investors in the clique during the year, adjusted for the institutional ownership. *Source: Thomson Reuters*
Clique size	A continuous variable of the firm level measure for the total number of institutional investors resides in cliques for a given firm. *Source: Thomson Reuters*
Insider abnormal returns	Insider abnormal returns is calculated utilizing the Alpha (-Alpha) from the four factor Carhart model estimated over the 180 days after the inside trading transaction (Carhart 1997). *Source: CRSP, Thomson Reuters, Fama-French Factors*
All insider trades	A continuous variable of the firm level measure for the natural logarithm of the number of insider traded plus 1 per quarter. *Source: Thomson Reuters*
Number of trades	A continuous variable of the firm level measure for the natural logarithm of the number of inside trades plus 1 per quarter. *Source: COMPUSTAT, CRSP,Thomson Reuters*
Trade size	The natural logarithm of the number of shares traded plus 1 aggregated on the date insider transaction occurred. *Source: Thomson Reuters*
Clique ownership	A continuous variable represents the sum of cliques' institutional ownership percentage at the firm-level. *Source: CRSP*
Institutional ownership	A continuous variable represents the percentage of the sum of the shares outstanding that is owned by financial institutions at the firm-level. *Source: CRSP*

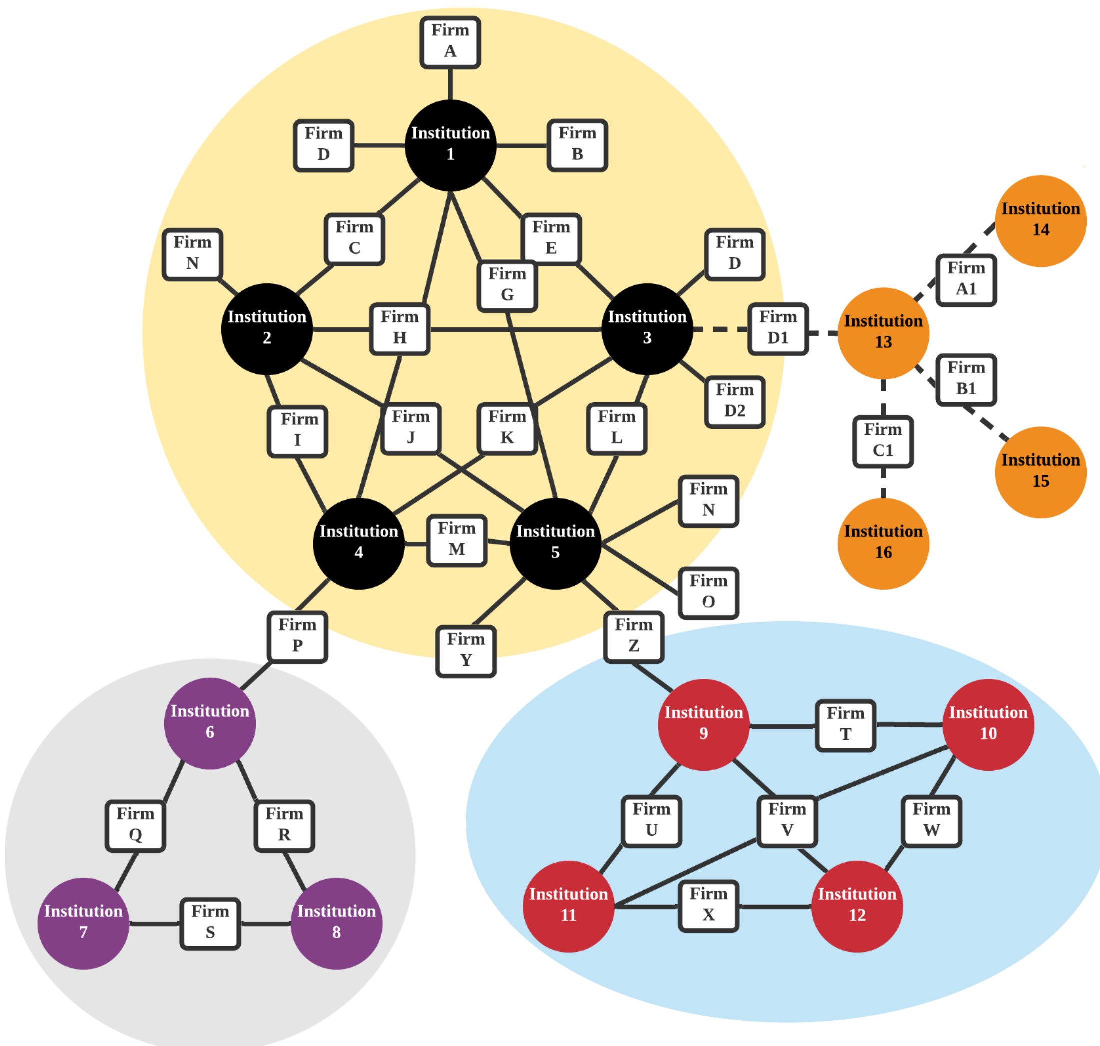
Variable	Definition and Data Source
Opportunistic insider	An indicator variable equal to 1 for opportunist insiders and equal to 0 for non-opportunistic insiders (Ali and Hirshleifer 2017).[16] *Source: COMPUSTAT, CRSP*
Senior executives trades	Trades made by insiders with the following Thomson Reuters insider role codes: AV; CEO; CFO; CI; CO; CT; EVP; GC; O; OB; OE; OP; OS; OT; OX; P; S; SVP; VP. *Source: Thomson Reuters*
Non senior executives trades	Trades are trades made by insiders with the following Thomson Reuters insider role codes: C; O; OS; OT; OX; TR. *Source: Thomson Reuters*
Directors trades	Trades made by insiders with the following Thomson Reuters insider role codes: CB; D; DO; H; OD; V; VC. *Source: Thomson Reuters*
Beneficial owners trades	Trades made by insiders with the following Thomson Reuters insider role codes: B; BC; BT. *Source: Thomson Reuters*
Changes in Clique Size	A continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the number of institutional investors in the clique in the prior year. *Source: Thomson Reuters*
Changes in Clique Size Scaled by Prior Clique Size	A continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the number of institutional investors in the clique in the prior year divided by the number of institutional investors in the clique in the prior year. *Source: Thomson Reuters*

[16] Ali and Hirshleifer 2017 use pre-quarterly earning announcement (QEA) trades to identify Opportunistic Insiders. A pre-QEA trade is a trade that occurs during the 21 trading days before the QEA, excluding the last two days before the QEA. The method compares the performance of the trades of Non-Opportunistic Insiders with Opportunistic Insiders at the same firm and during the same year to rule out the possibility that the results are driven by firm characteristics not associated with insider opportunism.

FIGURES

Figure 1.
Visual Representation of Cliques.

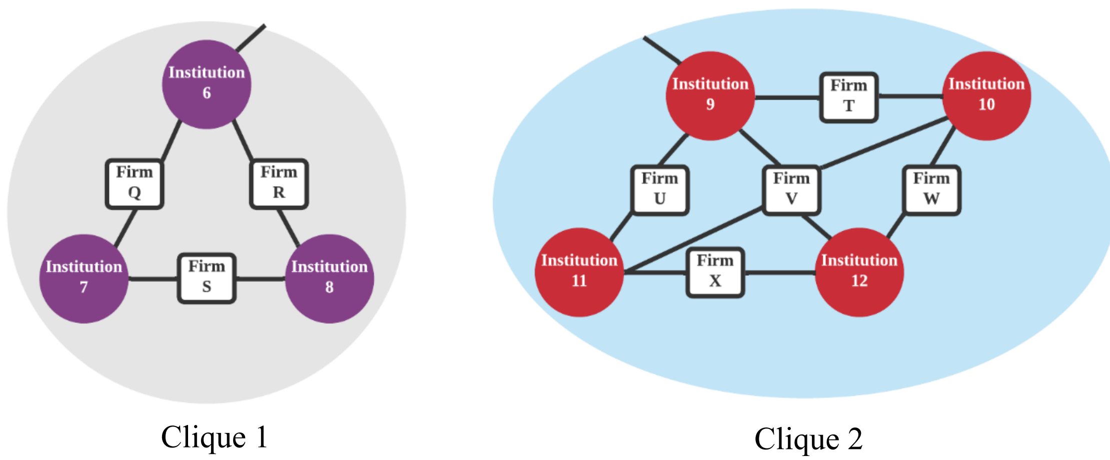
Examples of different clique sizes and institutions do not belong to any clique. Insiders I study in this paper are both Section 16 firm insiders and Section 16 institutional insiders



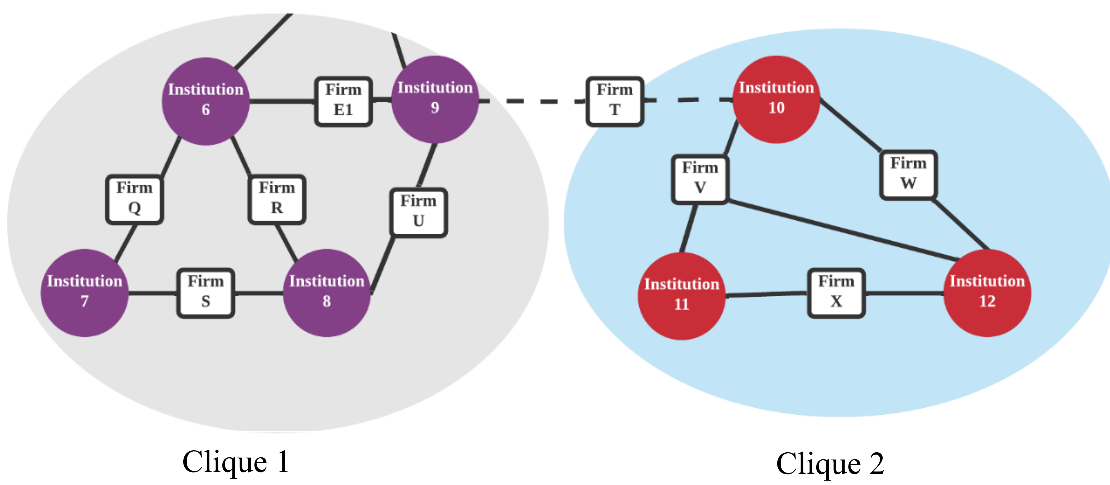
Clique 1 Clique 2

Figure 2.
Visual Representation of Clique Sizes Change.

Examples of Changes in Clique Sizes from the first period to the second period. In this example, Institution 9 decrease its investment in Firm V, Institution 11 decrease its investment in Firm U, and Institution 8 increase its investment in Firm U, leading Clique 1 and Clique 2 to change their clique sizes. Firm Q, Firm R, Firm S, and Firm E1 are marked for the benchmark (20% or above) Percent Clique Size Increase. Firm U and Firm T are not marked for the benchmark (20% or above) Percent Clique Size Increase since both Firm U and Firm T are associated with both clique size increase in Clique 1 and clique size decrease in Clique 2 in the second period. Insiders I study in this paper are both Section 16 firm insiders and Section 16 institutional insiders.



First Period



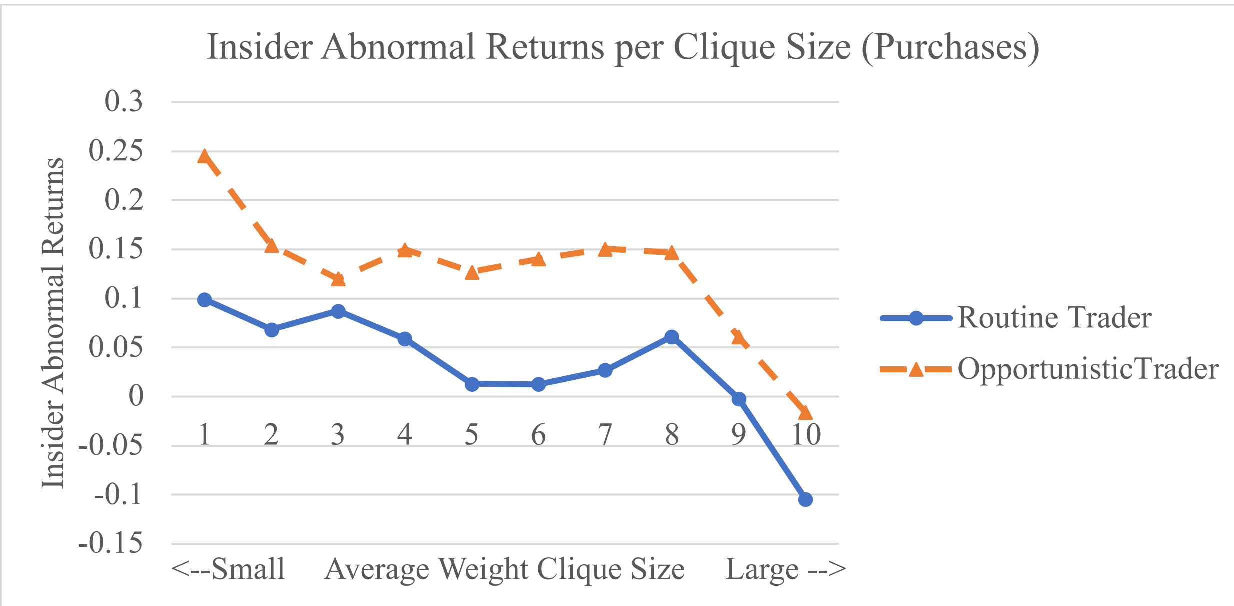
Second Period

Figure 3.
Institutional ownership concentration and weighted clique size over time.

This figure presents the time series of cross-sectional means of the concentration of institutional ownership and the weighted clique size at the firm-level. *IO Concentration* is the percentage owned by the five top institutions divided by institutional ownership as in Hartzell and Starks (2003). *Weighted Clique Size* is the firm-level measure for the number of institutional investors in the clique during the reporting period.

Figure 4A.
Insider abnormal returns per clique size (Purchases).

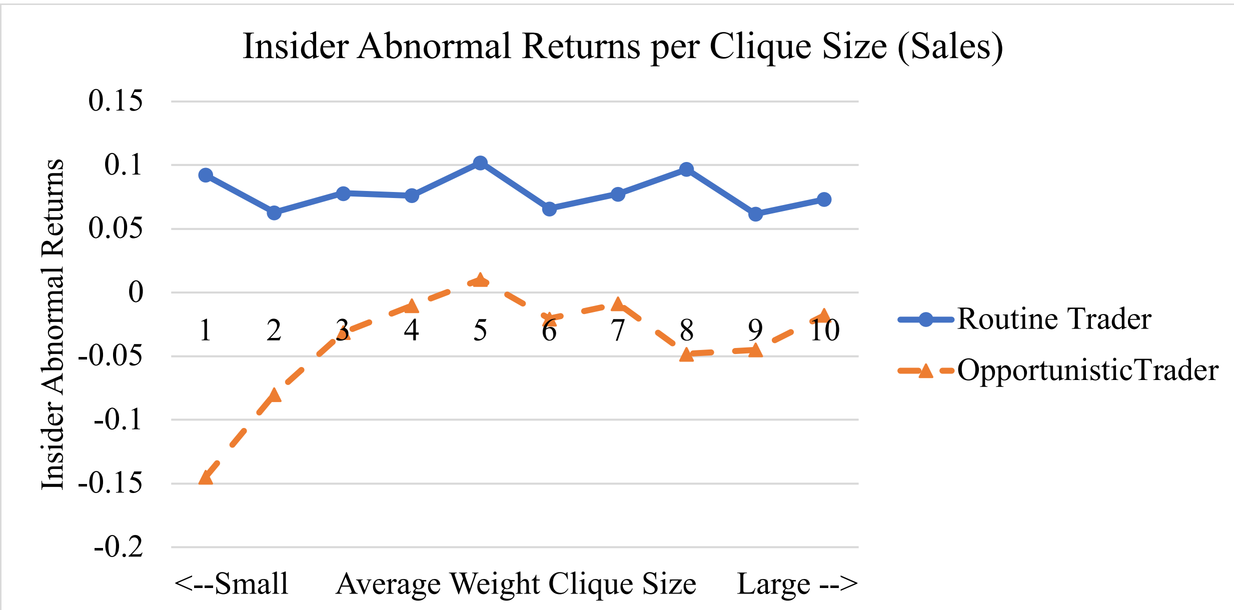
Weighted Clique Size is a continuous variable of the firm-level measure for the number of institutional investors in the clique during the year. *Insider Abnormal Returns* from purchases (sales) is calculated as the Alpha (-Alpha) from the four factor Carhart model estimated over the 180 days following the transaction (Carhart 1997). The average insider abnormal return on the purchase side per weighted clique size groups. The average insider abnormal return decreases for both routine and opportunistic traders as the average weighted clique size increases, suggesting the information dissemination effect is stronger in a larger clique.



Group	1	2	3	4	5	6	7	8	9	10
Average Weighted Clique Size	1.30	5.02	9.19	14.77	20.67	26.88	33.11	41.63	54.45	90.10

Figure 4B.
Insider abnormal returns per clique size (Sales).

Weighted Clique Size is a continuous variable of the firm-level measure for the number of institutional investors in the clique during the year. *Insider Abnormal Returns* from purchases (sales) is calculated as the Alpha (-Alpha) from the four factor Carhart model estimated over the 180 days following the transaction (Carhart 1997). The average insider abnormal return on the sale side per weighted clique size groups. The sales trades that receive negative abnormal returns are more than likely to be informative trades, while the sales trades that receive positive abnormal returns are more than likely not information incentive trades. The average insider abnormal return increases for opportunistic traders as the average weighted clique size increases, suggesting the information dissemination effect is stronger in a larger clique. The average insider abnormal return decreases slightly for routine traders as the average weighted clique size increases, suggesting most of their trades are not information motivated.



Group	1	2	3	4	5	6	7	8	9	10
Average Weighted Clique Size	5.95	18.89	29.26	37.39	43.70	50.09	56.59	64.78	74.18	95.33

TABLES

Table 1. Trade Level Sample Summary Statistics.

This table reports summary statistics for sample variables and categorizations associated with insider purchases and sales. *Weighted Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year. *Insider Abnormal Returns* from purchases (sales) is calculated as the Alpha (-Alpha) from the four factor Carhart model estimated over the 180 days following the transaction (Carhart 1997). *Number of Trades* is a continuous variable of the firm level measure for the natural logarithm of the number of inside trades plus 1 per quarter. *Trade Size* is the natural logarithm of the number of shares traded plus 1 aggregated on the date insider transaction occurred. *Institutional Ownership Ratio* is a continuous variable represents the percentage of shares outstanding that is owned by financial institutions. *Opportunistic Insider Returns* is an indicator variable equal to 1 for opportunist insiders and equal to 0 for non-opportunist insiders (Ali and Hirshleifer 2017).*Senior Executives* trades are trades made by insiders with the following Thomson Reuters insider role codes: AV; CEO; CFO; CI; CO; CP; CT; EVP; GC; O; OB; OE; OP; OS; OT; OX; P; S; SVP; VP. *Non-Senior Executives* trades are trades made by insiders with the following Thomson Reuters insider role codes: C; O; OS; OT; OX; TR. *Directors* trades are trades made by insiders with the following Thomson Reuters insider role codes: CB; D; DO; H; OD; V; VC. *Beneficial owners* trades are trades made by insiders with the following Thomson Reuters insider role codes: B; BC; BT.

	Purchases		Sales	
	Max. (128,779)	Observations	Max. (357,342)	Observations
	Mean	St. Dev	Mean	St. Dev
	(1)	(2)	(3)	(4)
Mean Value:				
Weighted clique size	29.642	26.202	47.590	25.694
Weighted clique size (Opportunistic Insiders)	38.138	30.993	43.778	27.076
Weighted clique size (Non Opportunistic Insiders)	27.390	24.284	48.417	25.308
Clique size	43.535	40.537	76.049	53.546
Clique size (Opportunistic Insiders)	38.187	34.509	52.513	36.329
Clique size (Non Opportunistic Insiders)	44.952	41.875	81.155	55.287
Insider abnormal returns	0.052	0.233	0.057	0.213
Insider abnormal returns (Opportunistic Insiders)	0.113	0.272	-0.042	0.277
Insider abnormal returns (Non Opportunistic Insiders)	0.037	0.219	0.077	0.189
Number of trades (logarithm size)	3.452	1.882	4.251	1.966
Trade size (logarithm size)	8.79	2.822	9.583	2.209
Institutional Ownership Ratio	1.179	3.868	0.673	2.045
Weighted Clique Size x Opportunistic Insider (Opportunistic Insiders)	38.112	30.911	43.702	26.861
Percentage of trades:				
Opportunistic insider	20.65%	0.405	17.40%	0.379
Trades by senior executives	31.34%	0.464	58.96%	0.492
Trades by non-senior executives	12.05%	0.325	28.89%	0.453
Trades by directors	40.19%	0.491	55.33%	0.497

Trades by beneficial owners	36.43%	0.481	13.81%	0.345

Table 2. Pearson Correlations.

Correlation coefficients, *Weighted Clique Size*, and Insider metrics. This presents results from the full sample with 485,959 observations and 29,487 firm-quarter. Pearson coefficients are presented below the diagonal. ***p<0.01, **p<0.05, *p<0.1. See the Appendix for full variable definitions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Weighted Clique Size	1												
(2) Clique Ownership	0.893***	1											
(3) Opportunistic Trader	-0.013***	-0.040***	1										
(4) Insider Abnormal Returns	-0.034***	-0.013***	-0.111***	1									
(5) Insider Abnormal Returns (Purchases)	-0.199***	-0.183***	0.131***	1***	1								
(6) Insider Abnormal Returns (Sales)	0.026***	0.054***	-0.214***	1.000***	.	1							
(7) Number of trades (logarithm size)	0.347***	0.246***	-0.041***	-0.001	-0.051***	0.017***	1						
(8) Number of trades (logarithm size – Purchases)	0.406***	0.262***	0.110***	-0.051***	-0.051***	-	1	1					
(9) Number of trades (logarithm size – Sales)	0.277***	0.176***	-0.089***	0.017***	-	0.017***	1.000***	-	1				
(10) Trade Sizes	0.309***	0.205***	-0.006***	0.024***	-0.070***	0.060***	0.700***	0.641***	0.721***	1			
(11) Trade Sizes (Purchases)	0.489***	0.274***	0.308***	-0.070***	-0.070***	-	0.641***	0.641***	.	1	1		
(12) Trade Sizes (Sales)	0.230***	0.161***	-0.122***	0.060***	-	0.060***	0.719***	.	0.721***	1.000	.	1	
(13) Institutional Ownership Ratio	-0.006***	0.015***	0.049***	0.027***	0.014***	0.041***	-0.062***	0.038***	-0.107***	-0.020***	0.096***	-0.098***	1

Table 3. Panel A Weighted Clique Size Difference-in-Difference (DID) Analysis: Firm Joins a Clique.

This table reports coefficient estimates from DID tests of *Insider Abnormal Returns* on *Weighted Clique Size* when a firm exogenously joins a clique. My sample consists of insiders from Thomson Reuters Insider Data. *Insider Abnormal Returns* from purchases (sales) is calculated as the Alpha (-Alpha) from the four factor Carhart model (Carhart 1997) estimated over the 180 days following the transaction. *Weighted Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year. *Post Join* dummy is a dummy variable equals 1 for firms that join a clique and equal to 0 for firms that do not join a clique. The sample consists of observations three years prior to the date when a firm joins a clique and three years after the date when a firm joins a clique. Columns (1) and (2) are OLS regressions of *Insider Abnormal Returns.* All models include firm and year fixed effects. Standard errors in all models are adjusted for clustering at the firm level. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Insider Abnormal Returns	
	Opportunistic Traders Only	
	Purchases	Sales
	(1)	(2)
Weighted Clique Size	-0.000	0.000
	(-0.460)	(0.382)
Post Join	-0.015	0.028
	(-0.226)	(0.469)
Weighted Clique Size x Post Join	-0.001	-0.004***
	(-0.422)	(-5.582)
Observations	1,015	5,270
Firm and Year Fixed Effects	Yes	Yes
R-squared	0.912	0.774
Adjust R-squared	0.899	0.766

Table 3. Panel B Changes in Clique Size Difference-in-Difference (DID) Analysis: Firm Joins a Clique.

This table reports coefficient estimates from DID tests of *Insider Abnormal Returns* on *Changes in Clique Size* when a firm exogenously joins a clique. My sample consists of insiders from Thomson Reuters Insider Data. *Insider Abnormal Returns* from purchases (sales) is calculated as the Alpha (-Alpha) from the four factor Carhart model (Carhart 1997) estimated over the 180 days following the transaction. *Changes in Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the number of institutional investors in the clique in the prior year. *Post Join* dummy is a dummy variable equals 1 for firms that join a clique and equal to 0 for firms that do not join a clique. The sample consists of observations three years prior to the date when a firm joins a clique and three years after the date when a firm joins a clique. Columns (1) and (2) are OLS regressions of *Insider Abnormal Returns.* All models include firm and year fixed effects. Standard errors in all models are adjusted for clustering at the firm level. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Insider Abnormal Returns	
	Opportunistic Traders Only	
	Purchases	Sales
	(1)	(2)
Changes in Clique Size	-0.002	0.001
	(-1.576)	(1.116)
Post Join	-0.034	-0.044
	(-0.839)	(-0.668)
Changes in Clique Size x Post Join	0.003	-0.012***
	(0.942)	(-7.476)
Observations	1,015	5,260
Firm and Year Fixed Effects	Yes	Yes
R-squared	0.913	0.771
Adjust R-squared	0.900	0.763

Table 3. Panel C Changes in Clique Size Scaled by Prior Clique Size Difference-in-Difference (DID) Analysis: Firm Joins a Clique.

This table reports coefficient estimates from DID tests of *Insider Abnormal Returns* on *Changes in Clique Size Scaled by Prior Clique Size* when a firm exogenously joins a clique. My sample consists of insiders from Thomson Reuters Insider Data. *Insider Abnormal Returns* from purchases (sales) is calculated as the Alpha (-Alpha) from the four factor Carhart model (Carhart 1997) estimated over the 180 days following the transaction. *Changes in Clique Size Scaled by Prior Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the number of institutional investors in the clique in the prior year divided by the number of institutional investors in the clique in the prior year. *Post Join* dummy is a dummy variable equals 1 for firms that join a clique and equal to 0 for firms that do not join a clique. The sample consists of observations three years prior to the date when a firm joins a clique and three years after the date when a firm joins a clique. Columns (1) and (2) are OLS regressions of *Insider Abnormal Returns.* All models include firm and year fixed effects. Standard errors in all models are adjusted for clustering at the firm level. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Insider Abnormal Returns	
	Opportunistic Traders Only	
	Purchases	Sales
	(1)	(2)
Changes in Clique Size Scaled by Prior Clique Size	0.010	-0.089***
	(0.288)	(-5.542)
Post Join	-0.026	-0.066
	(-0.596)	(-1.001)
Changes in Clique Size Scaled by Prior Clique Size x Post Join	-0.039	-0.136**
	(-0.394)	(-2.322)
Observations	1,015	5,260
Firm and Year Fixed Effects	Yes	Yes
R-squared	0.912	0.764
Adjust R-squared	0.899	0.756

Table 4. Panel A Weighted Clique Size Difference-in-Difference (DID) Analysis: Firm Exits a Clique.

This table reports coefficient estimates from DID tests of *Insider Abnormal Returns* on *Weighted Clique Size* when a firm exogenously exits a clique. My sample consists of insiders from Thomson Reuters Insider Data. *Insider Abnormal Returns* from purchases (sales) is calculated as the Alpha (-Alpha) from the four factor Carhart model (Carhart 1997) estimated over the 180 days following the transaction. *Weighted Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year. *Post Exit* dummy is a dummy variable equals 1 for firms that join a clique and equal to 0 for firms that do not join a clique. The sample consists of observations three years prior to the date when a firm exits a clique and three years after the date when a firm exits a clique. Columns (1) and (2) are OLS regressions of *Insider Abnormal Returns.* All models include firm and year fixed effects. Standard errors in all models are adjusted for clustering at the firm level. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Insider Abnormal Returns	
	Opportunistic Traders Only	
	Purchases	Sales
	(1)	(2)
Weighted Clique Size	-0.004***	-0.004***
	(-3.019)	(-12.947)
Post Exit	-0.160**	0.025
	(-2.346)	(0.825)
Weighted Clique Size x Post Exit	0.006***	0.002***
	(4.098)	(3.878)
Observations	2,117	10,242
Firm and Year Fixed Effects	Yes	Yes
R-squared	0.886	0.762
Adjust R-squared	0.873	0.751

Table 4. Panel B Changes in Clique Size Difference-in-Difference (DID) Analysis: Firm Exits a Clique.

This table reports coefficient estimates from DID tests of *Insider Abnormal Returns* on *Changes in Clique Size* when a firm exogenously exits a clique. My sample consists of insiders from Thomson Reuters Insider Data. *Insider Abnormal Returns* from purchases (sales) is calculated as the Alpha (-Alpha) from the four factor Carhart model (Carhart 1997) estimated over the 180 days following the transaction. *Changes in Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the number of institutional investors in the clique in the prior year. *Post Exit* dummy is a dummy variable equals 1 for firms that join a clique and equal to 0 for firms that do not join a clique. The sample consists of observations three years prior to the date when a firm exits a clique and three years after the date when a firm exits a clique. Columns (1) and (2) are OLS regressions of *Insider Abnormal Returns.* All models include firm and year fixed effects. Standard errors in all models are adjusted for clustering at the firm level. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Insider Abnormal Returns	
	Opportunistic Traders Only	
	Purchases	Sales
	(1)	(2)
Changes in Clique Size	-0.005***	-0.003***
	(-3.069)	(-6.992)
Post Exit	-0.009	0.105***
	(-0.154)	(5.821)
Changes in Clique Size x Post Exit	0.006***	0.003***
	(3.037)	(3.717)
Observations	2,117	10,240
Firm and Year Fixed Effects	Yes	Yes
R-squared	0.884	0.751
Adjust R-squared	0.871	0.740

Table 4. Panel C Changes in Clique Size Scaled by Prior Clique Size Difference-in-Difference (DID) Analysis: Firm Exits a Clique.

This table reports coefficient estimates from DID tests of *Insider Abnormal Returns* on *Changes in Clique Size Scaled by Prior Clique Size* when a firm exogenously exits a clique. My sample consists of insiders from Thomson Reuters Insider Data. *Insider Abnormal Returns* from purchases (sales) is calculated as the Alpha (-Alpha) from the four factor Carhart model (Carhart 1997) estimated over the 180 days following the transaction. *Changes in Clique Size Scaled by Prior Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the number of institutional investors in the clique in the prior year divided by the number of institutional investors in the clique in the prior year. *Post Exit* dummy is a dummy variable equals 1 for firms that join a clique and equal to 0 for firms that do not join a clique. The sample consists of observations three years prior to the date when a firm exits a clique and three years after the date when a firm exits a clique. Columns (1) and (2) are OLS regressions of *Insider Abnormal Returns.* All models include firm and year fixed effects. Standard errors in all models are adjusted for clustering at the firm level. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Insider Abnormal Returns	
	Opportunistic Traders Only	
	Purchases	Sales
	(1)	(2)
Changes in Clique Size Scaled by Prior Clique Size	-0.161**	-0.164***
	(-2.148)	(-8.048)
Post Exit	-0.032	0.093***
	(-0.493)	(4.962)
Changes in Clique Size Scaled by Prior Clique Size x Post Exit	0.186**	0.071*
	(2.284)	(1.883)
Observations	2,117	10,240
Firm and Year Fixed Effects	Yes	Yes
R-squared	0.883	0.752
Adjust R-squared	0.870	0.741

Table 5. Firm Level Dynamic Difference-in-Difference (DID) Analysis: Firm Joins a Clique.

This table reports coefficient estimates from Dynamic DID tests of *Insider Abnormal Returns* when a firm exogenously joins a clique. My sample consists of insiders from Thomson Reuters Insider Data. *Insider Abnormal Returns* from purchases (sales) is calculated as the Alpha (-Alpha) from the four factor Carhart model (Carhart 1997) estimated over the 180 days following the transaction. Join Clique equals 1 if the firm joins a clique during the sample period, and 0 otherwise. Dummies Year -2, Year -1, Year 1, and Year 2+ are indicator variables set to 1 if the firm-year is two years before, one year before, one year after, and two or more years after firm joins a clique, respectively (with Year 0 being the benchmark year). The columns (1) and (2) are Dynamic DID regressions of *Insider Abnormal Returns.* All models include firm and year fixed effects. Standard errors in all models are adjusted for clustering at the firm level. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Insider Abnormal Returns	
	Opportunistic Traders Only	
	Purchases	Sales
	(1)	(2)
Join Clique * Year -2	0.003	0.075***
	(0.081)	(4.564)
Join Clique * Year -1	0.064**	-0.006
	(2.072)	(-0.484)
Join Clique * Year 1	-0.152***	-0.080**
	(-5.688)	(-2.007)
Join Clique * Year +2	-0.130***	-0.023***
	(-6.790)	(-2.802)
Observations	27,334	65,417
R-squared	0.834	0.777
Adjust R-squared	0.821	0.767

Table 6. Firm Level Dynamic Difference-in-Difference (DID) Analysis: Firm Exits a Clique.

This table reports coefficient estimates from Dynamic DID tests of *Insider Abnormal Returns* when a firm exogenously exits a clique. My sample consists of insiders from Thomson Reuters Insider Data. *Insider Abnormal Returns* from purchases (sales) is calculated as the Alpha (-Alpha) from the four factor Carhart model (Carhart 1997) estimated over the 180 days following the transaction. Exit Clique equals 1 if the firm joins a clique during the sample period, and 0 otherwise. Dummies Year 2 -, Year -1, Year 1, and Year 2 are indicator variables set to 1 if the firm-year is two or more years before, one year before, one year after, and two years after firm exits a clique, respectively (with Year 0 being the benchmark year). The columns (1) and (2) are Dynamic DID regressions of *Insider Abnormal Returns.* All models include firm and year fixed effects. Standard errors in all models are adjusted for clustering at the firm level. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Insider Abnormal Returns	
	Opportunistic Traders Only	
	Purchases	Sales
	(1)	(2)
Exit Clique * Year -2	-0.098	-0.067
	(-1.274)	(-1.433)
Exit Clique * Year -1	-0.038	-0.024
	(-0.554)	(-0.648)
Exit Clique * Year 1	0.102***	0.095*
	(2.878)	(1.816)
Exit Clique * Year 2	0.389***	0.142***
	(8.677)	(3.603)
Observations	1,696	5,914
R-squared	0.916	0.755
Adjust R-squared	0.906	0.745

Table 7. The Relationship Between Changes in Clique Size and The Insider Trading Profits and Trading Patterns.

This table reports coefficient estimates from OLS tests of *Insider Abnormal Returns*, *Number of Trades*, and *Trade Size* on *Weighted Clique Size*. My sample consists of insiders from Thomson Reuters Insider Data. *Insider Abnormal Returns* from purchases (sales) is calculated as the Alpha (-Alpha) from the four factor Carhart model (Carhart 1997) estimated over the 180 days following the transaction. *Weighted Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year. *Number of Trades* is a continuous variable of the firm level measure for the natural logarithm of the number of inside trades plus 1 per quarter. *Trade Size* is the natural logarithm of the number of shares traded plus 1 aggregated on the date insider transaction occurred. The columns (1) and (2) are OLS regressions of *Insider Abnormal Returns.* The columns (3) and (4) are OLS regressions of *Number of Trades*. The columns (5) and (6) are OLS regressions of *Trade Size*. All models include firm and year fixed effects. Standard errors in all models are adjusted for clustering at the firm level. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Insider Abnormal Returns		Number of Trades		Trade Size	
	Opportunistic Traders Only		Opportunistic Traders Only		Opportunistic Traders Only	
	Purchases	Sales	Purchases	Sales	Purchases	Sales
	(1)	(2)	(3)	(4)	(5)	(6)
Weighted Clique Size	-0.004***	-0.002***	0.014***	0.008**	0.335***	2.002**
	(-3.612)	(-3.395)	(4.835)	(2.552)	(3.545)	(2.009)
Constant	0.240***	0.070**	3.250***	3.528***	729.683***	77.748*
	(6.213)	(2.202)	(29.855)	(26.897)	(202.856)	(1.785)
Observations	26,117	63,048	26,982	63,697	26,982	63,697
Number of firm_year	3,684	4,653	3,803	4,727	3,803	4,727
Adjust R-squared	0.0617	0.0459	0.0496	0.0183	0.0267	0.0645

Table 8. Panel A High Order Polynomial Tests for the Value of Information and the Information Dissemination Rate: Insider Abnormal Returns.

This table reports coefficient estimates from high order polynomial tests of *Insider Abnormal Returns*, *Number of Trades*, and *Trade Size* on *Weighted Clique Size.* My sample consists of insiders from Thomson Reuters Insider Data. *Insider Abnormal Returns* from purchases (sales) is calculated as the Alpha (-Alpha) from the four factor Carhart model (Carhart 1997) estimated over the 180 days following the transaction. *Weighted Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year. *Number of Trades* is a continuous variable of the firm level measure for the natural logarithm of the number of inside trades plus 1 per quarter. *Trade Size* is the natural logarithm of the number of shares traded plus 1 aggregated on the date insider transaction occurred. The columns (1) and (2) are OLS regressions of *Insider Abnormal Returns.* The columns (3) and (4) are high order polynomial regressions of *Insider Abnormal Returns*. All models include firm and year fixed effects. Standard errors in all models are adjusted for clustering at the firm level. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Insider Abnormal Returns		Insider Abnormal Returns	
	Opportunistic Traders Only		Opportunistic Traders Only	
	Purchases	Sales	Purchases	Sales
	(1)	(2)	(3)	(4)
Weighted Clique Size Centered	-0.004***	-0.002***	-0.004***	-0.002***
	(-3.363)	(-3.351)	(-3.602)	(-2.952)
Weighted Clique Size Centered x Weighted Clique Size Centered			-0.000	-0.000
			(-0.635)	(-1.467)
Constant	0.093***	-0.045***	0.105***	-0.031***
	(21.471)	(-58.724)	(5.095)	(-3.250)
Observations	26,117	63,048	26,117	63,048
Number of firm_year	3,684	4,653	3,684	4,653
Adjust R-squared	0.0443	0.0364	0.0450	0.0400

Table 8. Panel B High Order Polynomial Tests for the Value of Information and the Information Dissemination Rate: Number of Trades.

This table reports coefficient estimates from high order polynomial tests of *Insider Abnormal Returns*, *Number of Trades*, and *Trade Size* on *Weighted Clique Size.* My sample consists of insiders from Thomson Reuters Insider Data. *Insider Abnormal Returns* from purchases (sales) is calculated as the Alpha (-Alpha) from the four factor Carhart model (Carhart 1997) estimated over the 180 days following the transaction. *Weighted Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year. *Number of Trades* is a continuous variable of the firm level measure for the natural logarithm of the number of inside trades plus 1 per quarter. *Trade Size* is the natural logarithm of the number of shares traded plus 1 aggregated on the date insider transaction occurred. The columns (1) and (2) are OLS regressions of *Number of Trades.* The columns (3) and (4) are high order polynomial regressions of *Number of Trades*. All models include firm and year fixed effects. Standard errors in all models are adjusted for clustering at the firm level. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Number of Trades		Number of Trades	
	Opportunistic Traders Only		Opportunistic Traders Only	
	Purchases	Sales	Purchases	Sales
	(1)	(2)	(3)	(4)
Weighted Clique Size Centered	0.014***	0.014***	0.014***	0.007**
	(4.835)	(4.835)	(5.203)	(2.462)
Weighted Clique Size Centered x Weighted Clique Size Centered			0.000	0.000
			(0.599)	(0.455)
Constant	3.842***	3.842***	3.800***	3.834***
	(284.506)	(284.506)	(52.592)	(79.188)
Observations	26,982	26,982	26,982	63,697
Number of firm_year	3,803	3,803	3,803	4,727
Adjust R-squared	0.0496	0.0496	0.0503	0.0187

Table 8. Panel C High Order Polynomial Tests for the Value of Information and the Information Dissemination Rate: Trade Size.

This table reports coefficient estimates from high order polynomial tests of *Insider Abnormal Returns*, *Number of Trades*, and *Trade Size* on *Weighted Clique Size.* My sample consists of insiders from Thomson Reuters Insider Data. *Insider Abnormal Returns* from purchases (sales) is calculated as the Alpha (-Alpha) from the four factor Carhart model (Carhart 1997) estimated over the 180 days following the transaction. *Weighted Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year. *Number of Trades* is a continuous variable of the firm level measure for the natural logarithm of the number of inside trades plus 1 per quarter. *Trade Size* is the natural logarithm of the number of shares traded plus 1 aggregated on the date insider transaction occurred. The columns (1) and (2) are OLS regressions of *Trade Size.* The columns (3) and (4) are high order polynomial regressions of *Trade Size*. All models include firm and year fixed effects. Standard errors in all models are adjusted for clustering at the firm level. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Trade Size		Trade Size	
	Opportunistic Traders Only		Opportunistic Traders Only	
	Purchases	Sales	Purchases	Sales
	(1)	(2)	(3)	(4)
Weighted Clique Size Centered	0.026***	0.018***	0.025***	0.023***
	(4.357)	(3.970)	(4.269)	(4.536)
Weighted Clique Size Centered x Weighted Clique Size Centered			-0.000	-0.000**
			(-1.271)	(-2.457)
Constant	12.934***	13.418***	13.093***	13.577***
	(463.072)	(3,419.574)	(96.688)	(208.687)
Observations	26,982	63,691	26,982	63,691
Number of firm_year	3,803	4,723	3,803	4,723
Adjust R-squared	0.0234	0.0258	0.0247	0.0320

Table 9. Alternative Clique Size Measure: Changes in Clique Size.

This table reports coefficient estimates from OLS tests of *Insider Abnormal Returns*, *Number of Trades*, and *Trade Size* on *Changes in Clique Size*. My sample consists of insiders from Thomson Reuters Insider Data. *Insider Abnormal Returns* from purchases (sales) is calculated as the Alpha (-Alpha) from the four factor Carhart model (Carhart 1997) estimated over the 180 days following the transaction. *Changes in Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the number of institutional investors in the clique in the prior year. *Number of Trades* is a continuous variable of the firm level measure for the natural logarithm of the number of inside trades plus 1 per quarter. *Trade Size* is the natural logarithm of the number of shares traded plus 1 aggregated on the date insider transaction occurred. The columns (1) and (2) are OLS regressions of *Insider Abnormal Returns.* The columns (3) and (4) are OLS regressions of *Number of Trades*. The columns (5) and (6) are OLS regressions of *Trade Size*. All models include firm and year fixed effects. Standard errors in all models are adjusted for clustering at the firm level. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Insider Abnormal Returns		Number of Trades		Trade Size	
	Opportunistic Traders Only		Opportunistic Traders Only		Opportunistic Traders Only	
	Purchases	Sales	Purchases	Sales	Purchases	Sales
	(1)	(2)	(3)	(4)	(5)	(6)
Changes in Clique Size	-0.002***	-0.003***	0.008***	0.008***	1.861***	1.219***
	(-5.692)	(-17.752)	(4.322)	(8.158)	(5.463)	(7.358)
Observations	25,270	62,283	26,093	62,914	26,093	62,914
R-squared	0.834	0.832	0.975	0.895	0.996	0.927
Adjust R-squared	0.820	0.825	0.973	0.890	0.996	0.924

Table 10. Alternative Clique Size Measure: Changes in Clique Size Scaled by Prior Clique Size.

This table reports coefficient estimates from OLS tests of *Insider Abnormal Returns*, *Number of Trades*, and *Trade Size* on *Changes in Clique Size Scaled by Prior Clique Size*. My sample consists of insiders from Thomson Reuters Insider Data. *Insider Abnormal Returns* from purchases (sales) is calculated as the Alpha (-Alpha) from the four factor Carhart model (Carhart 1997) estimated over the 180 days following the transaction. *Changes in Clique Size Scaled by Prior Clique Size* is a continuous variable of the firm level measure for the number of institutional investors in the clique during the year minus the number of institutional investors in the clique in the prior year divided by the number of institutional investors in the clique in the prior year. *Number of Trades* is a continuous variable of the firm level measure for the natural logarithm of the number of inside trades plus 1 per quarter. *Trade Size* is the natural logarithm of the number of shares traded plus 1 aggregated on the date insider transaction occurred. The columns (1) and (2) are OLS regressions of *Insider Abnormal Returns.* The columns (3) and (4) are OLS regressions of *Number of Trades*. The columns (5) and (6) are OLS regressions of *Trade Size*. All models include firm and year fixed effects. Standard errors in all models are adjusted for clustering at the firm level. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Insider Abnormal Returns		Number of Trades		Trade Size	
	Opportunistic Traders Only		Opportunistic Traders Only		Opportunistic Traders Only	
	Purchases	Sales	Purchases	Sales	Purchases	Sales
	(1)	(2)	(3)	(4)	(5)	(6)
Changes in Clique Size Scaled by Prior Clique Size	-0.106***	-0.077***	-0.020	0.384***	26.440**	57.320***
	(-6.051)	(-11.954)	(-0.197)	(9.395)	(2.145)	(11.517)
Observations	25,270	62,283	26,093	62,914	26,093	62,914
R-squared	0.834	0.831	0.975	0.895	0.996	0.927
Adjust R-squared	0.820	0.824	0.973	0.890	0.996	0.924