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Information networks: Evidence from illegal insider trading tips☆

Kenneth R. Ahern

Marshall School of Business, University of Southern California, 701 Exposition Boulevard, Ste. 231, Los Angeles, CA 90089-1422, USA

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ABSTRACT

This paper exploits a novel hand-collected data set to provide a comprehensive analysis of the social relationships that underlie illegal insider trading networks. I find that inside information flows through strong social ties based on family, friends, and geographic proximity. On average, inside tips originate from corporate executives and reach buy-side investors after three links in the network. Inside traders earn prodigious returns of 35% over 21 days, with more central traders earning greater returns, as information conveyed through social networks improves price efficiency. More broadly, this paper provides some of the only direct evidence of person-to-person communication among investors.

1. Introduction

Though it is well established that new information moves stock prices, it is less certain how information spreads among investors. Shiller and Pound (1989) propose that information spreads among investors following models of disease contagion. More recent papers model the transmission of information through direct communication between investors (Stein, 2008; Han and Yang, 2013; Andrei and Cujean, 2015). The predictions of these models suggest that the diffusion of information over social networks is crucial for many financial outcomes, such as heterogeneity in trading profits, market efficiency, momentum, and local bias.

Empirically identifying the diffusion of information through social networks is challenging because direct observations of personal communication among investors is rare. Instead, existing evidence relies on indirect proxies of social interactions, such as geographic proximity (Hong, Kubik and Stein, 2005; Brown, Ivković, Smith and Weisbenner, 2008), common schooling (Cohen, Frazzini and Malloy, 2008; 2010), coworkers (Hvide and Östberg, 2015), and correlated stock trades (Ozsoylev, Walden, Yavuz and Bildak, 2014). While these proxies might reflect social interactions, they could also reflect homophily, in which investors act alike because they share similar backgrounds, not because they share information. In addition, indirect proxies cannot distinguish the quality of information that investors

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E-mail address: kenneth.ahern@marshall.usc.edu

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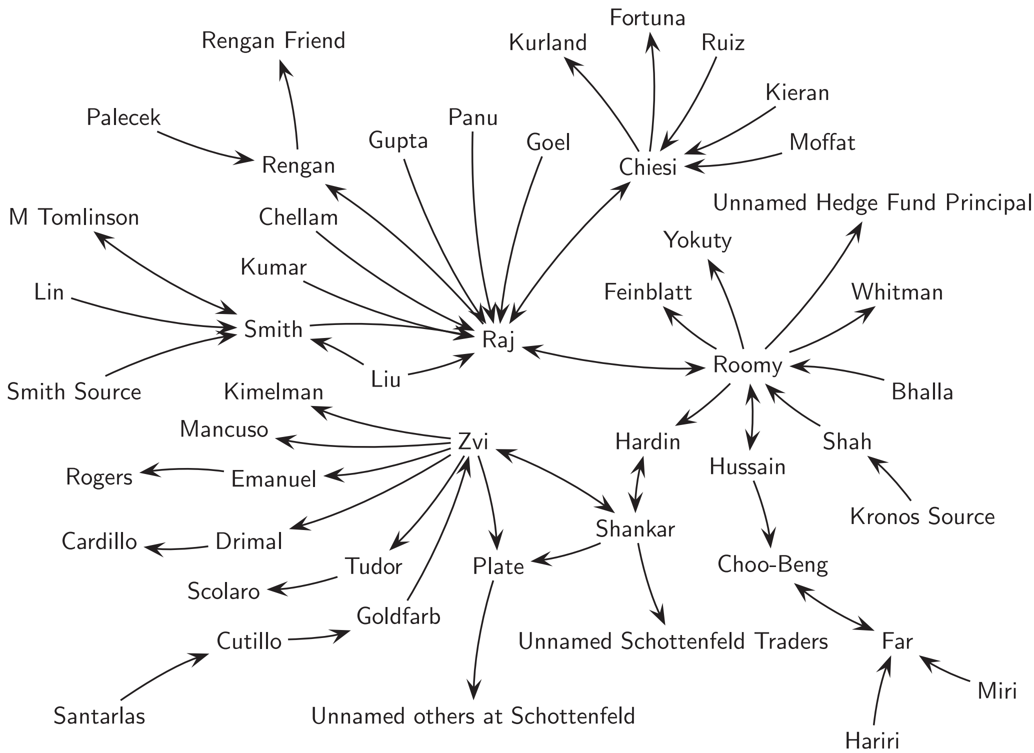

Fig. 1. Raj Rajaratnam network. This figure represents the illegal insider trading network centered on Raj Rajaratnam. Arrows represent the direction of information flow. Data are from SEC and DOJ case documents from 2009 to 2013, plus additional source documents to identify individuals not named in the SEC and DOJ documents.

share. For example, the information could be an informed investor's private observations, a noise trader's uninformative beliefs, or news reported in public media sources. Different quality information is likely to have different implications for financial outcomes.

In this paper, I address these challenges by studying one particular form of information sharing: illegal insider trading. Though sharing illegal insider tips does not represent all forms of information sharing, it is an attractive setting for this study. First, legal documents in insider trading cases provide direct observations of person-to-person communication, including details on the social networks between traders. This means I do not rely on indirect proxies of social interaction. Second, by definition, insider trading is only illegal if people share material, nonpublic information. This means that I exclude irrelevant, public information. Finally, illegal insider trading represents an important component of the market. In particular, Augustin, Brenner and Subrahmanyam (2014) estimate that 25% of merger and acquisition (M&A) announcements are preceded by illegal insider trading.

In total, I identify 183 insider trading networks using hand-collected data from all of the insider trading cases filed by the Securities and Exchange Commission (SEC) and the Department of Justice (DOJ) between 2009 and 2013. The case documents provide highly detailed data on both inside traders and people who shared information but did not trade securities themselves. (For brevity, I use the term 'inside trader' to refer to both types of people.) The data include biographical information, descriptions of social relationships, the nature and timing of information, and the amount and timing of insider trades. The data cover 1,139 insider tips shared by 622 inside traders who made an aggregated $928 million in illegal profits.

To illustrate how inside information flows across a network of traders, Fig. 1 represents the insider trading network centered around Raj Rajaratnam, the former hedge fund manager of the Galleon Group. Each arrow in the figure represents the flow of information from a tipper to a tippee. For example, one tip began in March 2007, when a credit analyst at UBS (Kronos Source) learned through his job that the software company Kronos would be acquired. On March 14, the Kronos source tipped this information to his friend, Deep Shah. On the same day, Shah tipped the information to his roommate's cousin, Roomy Khan. Khan then tipped two former business associates: Jeffrey Yokuty and his boss, Robert Feinblatt; and two friends: Shammara Hussain and Thomas Hardin. Hardin tipped his friend, Gautham Shankar, who tipped Zvi Goffer, David Plate, and others. Goffer then tipped his long-time friend, Joseph Mancuso. After the acquisition was officially announced on March 23, this group of inside traders had realized gains of $2.9 million in nine days. Fig. 1 shows that these insiders are a small part of a larger network of 50 inside traders.

The paper is organized as follows. First, I provide an in-depth demographic profile of inside traders. Then, I predict that the underlying social networks of inside traders influence three outcomes: 1) the spread of inside information, 2) the impact of insider trading on stock prices, and 3) insiders' individual trading gains. Finally, I discuss the generalizability of the findings.

I begin with a profile of inside traders. The average inside trader is 43 years old and about 90% of inside traders in the sample are men. The most common occupation among inside traders is top executive, including chief executive officers (CEOs) and directors, accounting for 17% of known occupations. There are a significant number of buy-side investment managers (10%) and analysts (11%), as well as sell-side professionals, such as lawyers, accountants, and consultants (10%). The sample also includes non-"Wall Street" types, such as small business owners, doctors, engineers, and teachers.

Inside traders share information about specific corporate events that have large effects on stock prices. Mergers account for 51% of the sample, followed by earnings announcements, accounting for 26%. The remaining events include clinical trial and regulatory announcements, sale of new securities, and operational news, such as CEO turnovers. The firms in which inside traders invest tend to be large high-tech firms with a median market equity of $1 billion.

Trading in advance of these events yields large returns. Across all events, the average stock return from the date of the original leak through the official announcement date of the event is 35%, over an average holding period of 21 trading days. M&A tips generate average returns of 43% in 31 days. Earnings tips generate relatively smaller returns of 14% in 11 days. Of the people who trade securities, the median inside trader invests about $200,000 per tip, though some invest as little as a few thousand dollars, and others invest hundreds of millions. For these investments, the median trader earns about $72,000 per tip.

The first prediction I investigate is that social networks influence the spread of inside information. Insiders have an incentive to share information to win favor with family, friends, and employers. However, sharing information increases their chances of prosecution. Thus, insiders are likely to share information with people they trust the most. This means that inside information is likely to spread through close social relationships. To test this hypothesis, I measure the closeness of inside traders based on the strength of their social relationships, their geographic proximity, and whether they share common education, ancestry, age, and gender.

First, I find that inside traders are connected through close social relationships. Of the 461 pairs of tippers and tippees in the sample, 23% are family members, 35% are friends, and 35% are business associates, including pairs that have both family and business links. Within families, the closest family members are also the most likely to share information: siblings and parents.

Next, I find that inside traders live close to each other. The median distance between a tipper and his tippee is 26 miles. This finding supports the idea that inside traders share information through face-to-face interactions, and it validates the use of geographic proximity as a proxy for information sharing (e.g., Hong, Kubik and Stein, 2005). Next, many inside traders share a common educational background. Of the pairs with available data, 64% met before college, and 16% met in college or graduate school. These results provide validation that information flows over school-ties, as proposed in Cohen, Frazzini and Malloy (2008). In addition, inside traders tend to share a common surname ancestry, even excluding family members. This finding is consistent with less trust in cross-cultural relations (Guiso, Sapienza and Zingales, 2009).

One concern with this analysis is that I only observe connections between people who received inside information. Ideally, I would also observe a counterfactual social network of people who could have received a tip, but did not. This would allow me to identify which types of social relationships are more likely to influence the spread of inside information. To address this concern, I use social network data from the massive LexisNexis Public Records Database (LNPRD) to identify family members and associates. For each tipper in the sample, I observe a broad social network, including people not listed as tippees in the SEC and DOJ documents. Including these counterfactual observations, I find that inside traders tend to share information with people that are closer in age and of the same gender. Among family relationships, inside traders are more likely to tip their fathers and brothers than mothers and sisters.

Next, I find that inside information flows across the network in specific patterns. Information tends to flow from subordinates to bosses, from younger tippers to older tippees, and from children to parents. These patterns suggest that social hierarchies may lead lower status tippers to try to win favor with higher status tippees. As information flows away from the original source, business associates become more prevalent than friends and family, and buy-side managers and analysts become more prevalent than corporate insiders. However, buy-side traders only account for the majority of tippees after three links in the network, on average. Thus, information eventually reaches well-capitalized and sophisticated traders, but not immediately.

To complete the investigation of the spread of inside information, I study the structure of insider trading networks. Of 183 insider networks in the sample, 59 contain only one person. On the other end of the spectrum, the network surrounding the hedge fund SAC Capital has 64 members. In the cross-section, larger networks are less dense with fewer clusters of links. This means that, similar to other criminal networks, insider networks sprawl outward like a tree's branches, rather than through one central node.

Taken together, these results imply that underlying social relationships influence the spread of inside information. In particular, information flows locally through clusters of inside traders with similar backgrounds and close social relationships. This finding is consistent with Stein's (2008) prediction that valuable information remains local, even though social networks are broad. This finding is also consistent with the importance of trust in criminal networks (Morselli, 2009).

The second prediction I investigate is that the social networks of inside traders influence stock prices. First, I show that insider trading moves stock prices toward their fundamental values. In panel regressions that control for event-firm fixed effects, event-day fixed effects, trading volume, and daily risk factors, I find that on days with greater insider trading, stock returns are significantly higher for positive events and significantly lower for negative events. These results show that the flow of information over social networks increases market efficiency.

Next, I test whether the backgrounds of inside traders are related to the price impact of their trades. For example, the trades of an older investor who receives information from a family member might have a stronger impact on stock prices than the trades of a younger investor who receives information from a friend. Alternatively, since the market is anonymous, the backgrounds of traders may not have any effect on market prices. I find that most characteristics of inside traders, such as age, occupation, and network position are unrelated to the price impact of trading. These results imply that while social networks are important conduits for the transmission of material information, prices reflect the information, not the provenance of the information.

The final prediction I investigate is that social networks influence insiders' individual trading gains. In cross-sectional regressions, I find that more central inside traders in larger networks realize both greater returns and profit. These results are consistent with the theoretical models of Ozsoylev and Walden (2011) and Walden (2013), in which more central insiders exploit their information advantage to earn greater profits. It is important to note that because my results show that centrality is related to returns, not just profit, it implies that more central inside traders receive more valuable information, not just more information.

Though insider trading is an attractive setting for studying the flow of information, its primary drawback is generalizability. First, my results might not apply to the flow of less factual or public information. Without fear of prosecution, investors are likely to share public information more broadly than inside information. Second, like most studies of criminal activity, my results might not generalize to the general population of illegal inside traders. I attempt to address this concern in a couple of ways. First, as mentioned above, I identify counterfactual observations of relatives and associates not named by regulators. Second, based on biases in the detection methods used by regulators, I infer that my sample tends to under-represent small, opportunistic traders and over-represent traders that are more likely to impact stock prices: wealthy CEOs and fund managers in larger networks who invest larger sums.

This paper contributes to two lines of research. First, this paper contributes to research on the importance of social networks for the diffusion of information among investors, discussed above. This paper provides some of the first direct evidence that investors share material, nonpublic information across close social connections. In addition, this is one of the first papers to show that the spread of information across social networks affects market efficiency, not just individual trading gains. Finally, to my knowledge, this is the first paper that identifies a counterfactual social network among traders and is the first to exploit the vast social network data in the LNPRD.

Second, this paper provides the most detailed description of illegal insider trading to date. The most closely related paper is Meulbroek (1992), which uses SEC cases from the 1980s to show that insider trading affects takeover prices. Other papers focus on the effect of illegal insider trading on merger run-ups, including Jarrell and Poulsen (1989), Schwert (1996), and Fishe and Robe (2004), or the prevalence of insider trading, including Augustin, Brenner and Subrahmanyam (2014), Bhattacharya and Daouk (2002), and Del Guercio, Odders-White and Ready (2013). Bhattacharya (2014) provides an overview of the literature on insider trading. In contrast to these papers, I provide new evidence on the profile of inside traders and the social connections that underlie their networks.

Finally, though this paper does not focus on the legal issues surrounding insider trading laws, the results inform the current policy debate about the definition of illegal insider trading. In December 2014, the U.S. Second Circuit Court of Appeals overturned the guilty verdicts of Anthony Chiasson and Todd Newman. A key part of Chiasson and Newman's defense was that they were separated from the original source by many links in the network. My results show that traders who are many links removed from the original source tend to be well-capitalized buy-side investors who make many insider trades. This means that under the new definition of illegal insider trading, the biggest inside traders are less likely to be convicted of a crime.

2. Data sources

2.1. Legal documents

The primary sources of data in this paper are legal documents filed by the SEC and the DOJ as part of illegal insider trading cases. To identify SEC cases, I record the titles of all of the cases reported in the SEC's annual summaries of enforcement actions, "Select SEC and Market Data," for each fiscal year between 2009 and 2013, the most recent publication date. I start data collection in 2009 because the SEC and DOJ both had regime shifts around 2008 in enforcement and investigative power. In particular, President Obama appointed a new chair of the SEC in January 2009 and the DOJ brought its first case that used wiretap evidence in 2009.[1] Because some cases involve multiple SEC violations, an insider trading case could be categorized in a different section of the "Select SEC and Market Data" publication. Therefore, I also search in Factiva for SEC publications that include the text "insider trading." This search finds seven cases that involve insider trading that are categorized as Investment Advisers/Investment Companies or Issuer Reporting and Disclosure cases. The Factiva search also identifies cases filed prior to fiscal year 2009 which were amended after 2009, and new cases filed during calendar year 2013, but after the end of fiscal year 2013. I include all of these cases in the sample. I drop 26 cases of fraud in which insiders release false or misleading information, such as pump and dump cases. These cases are fundamentally different because the insider wants to

[1] More details of the regime shift are discussed in the Internet Appendix.

broadcast false information as widely as possible, whereas in the sample cases, inside traders share factual information locally. I also drop nine SEC cases that do not name specific individuals. These cases are based on suspicious trading activity, typically from an overseas trading account. All cases were filed in calendar years 2009 to 2013, except one case that was filed in December 2008. I include this case because the DOJ case was filed in 2009.

Unlike the SEC, the DOJ does not provide summary lists of all the insider trading cases it brings. Therefore, I search Factiva for all DOJ press releases with the words "insider trading" and record the name of the case from the press release. In the sample, only two cases filed by the DOJ are not also charged by the SEC.

I use a number of sources to collect the original case documents. First, I search the SEC's website for official documents, the most useful of which is a civil complaint. Complaint filings typically include a detailed narrative history of the allegations, including biographies of defendants, trading records, and descriptions of the relationships between tippers and tippees to justify the allegations. Some cases are not available on the SEC web page. For these cases and for all DOJ cases, I search for the case documents using Public Access to Court Electronic Records (PACER). The most useful DOJ documents are the criminal complaints and "information" documents. These are similar to civil complaints, but contain less information. Transcripts of hearings, while potentially informative, are typically not available on PACER.

The search procedure yields 335 primary source documents comprising 5,423 pages supporting 203 SEC cases and 114 DOJ cases. There are 2.6 defendants in the average SEC case and 1.4 in the average DOJ case. Some people named in the documents were not charged with a crime and some people did not trade securities. However, everyone named in the documents is alleged to have shared material, nonpublic information. In addition, cases may also cover multiple events of one or many firms. In some instances, the same event is covered in unrelated cases in which different sets of inside traders shared information about the same event.

Because the documents provide data in narrative histories, they must be recorded by hand. Manually reading each individual case is also necessary to sort out the identities of all of the inside traders named in the cases. In particular, in many DOJ documents, co-conspirators remain anonymous. Some co-conspirators' identities are revealed in future cases, but other co-conspirators' identities are never revealed by the DOJ. However, these same people are often named in the SEC documents. Therefore, it is necessary to read all of the cases and their amendments in order to piece together the identities of as many people as possible. For instance, in many cases it is easy to infer who the co-conspirator is by the description of their job and relationship to the defendant in connection with another DOJ case in which the co-conspirator is the named defendant. In some instances, the identities of certain inside traders are never revealed. In these cases, I rely on investigative journalism in media reports, when available, that uncover the identities of people that the SEC and DOJ do not name explicitly.

From the primary source documents, I record five key types of information. First, I record the names, locations, employers, and ages of all people named in the document. Second, I record the social relationships between tippers and tippees, including family relations, friendships, and coworker relationships. Third, I record the original source of the information and how the source received the information. For instance, the documents might explain that a lawyer was assigned to work on an upcoming acquisition. Fourth, I record the timing of information flows. This includes the days when tippers and tippees communicated in person, by phone, or electronically. In some cases, the documents record the timing of phone calls to the minute. Finally, I record detailed descriptions of trading behavior, including the dates of purchases and sales, the amount purchased, the types of securities purchased (e.g., shares or options), and the profits from the sales.

2.2. LexisNexis Public Records Database

The second major source of data in this paper is the LexisNexis Public Records Database (LNPRD). The LNPRD includes a wide array of biographical information, including age, address, real property ownership, employers, licenses, liens, bankruptcies, and criminal records. With over 300 million people from the US in the database, including living and dead, this is the most comprehensive database for demographic information on the general public. Because the case documents include name, age, and location, I am able to identify people named in the filing documents with a high degree of accuracy. For instance, in one case, the SEC complaint only states, "Richard Vlasich is a friend of Michael Jobe and resides in Fort Worth." I find the entry for Vlasich on LNPRD using his name, city, and approximate age. The LNPRD data state that his employer is Vlasich Associates. Using this information, I find his resume on an online professional networking site, which describes his role in Vlasich Associates as the owner of a small real estate business.

I also record data on family members and person associates from the LNPRD. The specific type of familial relation is not identified in the LNPRD, though the data do indicate first or second degree connections and through whom the connections run. For example, using married and maiden names, I identify wives as women who are roughly the same age as the inside trader who also share a history of common addresses and own property jointly. The second degree connections through a wife could include the wife's parents or siblings, which I can identify by age, surname, and address of the second degree relatives. If a familial relationship cannot be identified, I record it as unknown. Person associates are non-family members with whom an inside trader shares a relationship. The exact algorithm for identifying person associates is proprietary to LexisNexis using their vast public and private records database. In general, these are people with whom an inside trader may have shared an address, had business dealings, or is connected in some other way through primary source records. The Internet Appendix provides more details on the LNPRD.

2.3. Additional sources of data

Not all documents contain all information. In particular, the job titles of many people are not listed. To find occupations, I search online professional social networking sites. Using the reported employer and location helps to identify the particular person on these sites. However, because people charged with insider trading often wish to hide their connection with the illegal trading charges, they may not list their old employer on online resumes. In these cases I use the employment records in the LNPRD. However, the LNPRD does not report job titles. To overcome this obstacle, I use the Internet Archive's "Wayback Machine" to search company websites on dates before the insider trading charges were filed to identify job titles and other biographical information. Finally, I use web searches to try to find any remaining data.

In addition to the case documents and the LNPRD, I estimate home values as a proxy for wealth using estimates from the online real estate website, Zillow.com. I also record the gender of every person in the data set based on the person's first name. For unfamiliar names, I rely on two databases: namepedia.org and genderchecker.com. Finally, I record the ancestry of every inside trader's surname using the Onomap database, under the assumption that kinship is an important determinant of social networks (McPherson, Smith-Lovin and Cook, 2001). The Onomap database codes surnames into 14 different ethnic origins.[2]

3. Illegal insider trading events and firms

3.1. Events

The sample includes 465 events. The earliest event is in 1996, and the most recent is in 2013, though 89% of the events occur between 2005 and 2012. The cases that involve insider trading in the earlier periods typically concern a defendant that is charged with a long-running insider trading scheme. In 25 events, I cannot identify an announcement date because the SEC and DOJ documents do not specify a specific event.

Table 1 presents statistics on the frequency of different types of events, stock returns, and holding periods surrounding insider trading. Panel A shows that the most common type of event with 239 instances, or 51% of all events, is a merger or acquisition (M&A). The large majority of these events are acquisitions, though I also include 12 joint ventures, licensing agreements, strategic alliances, and restructuring events, plus eight events related to developments in merger negotiations, such as the collapse of a deal. Of the 219 acquisition events, informed investors traded in the target's stock in 216 cases, and the acquirer's stock in just three cases.

The next most common type of event in the sample is earnings-related announcements, with 123 events, or 26% of the sample. The large majority of these events (112 events) are regularly scheduled earnings announcements. The rest of the earnings-related events are announcements of earnings restatements and earnings guidance.

The remaining 22% of the sample comprises drug clinical trial and regulatory announcements (8.0%), the sale of securities (7.5%), general business operations, such as the resignation or appointment of a senior officer, employee layoffs, and announcements of new customer-supplier contracts (2.8%), and other announcements (3.9%), such as analysts reports, dividend increases, and the addition to a stock index. The other events category also contains events that are not specified in the SEC and DOJ documents. All but two of the sale of securities events involve private investment in public equity transactions, with the vast majority for Chinese firms traded in the United States.

Table 1 also distinguishes whether the inside information contains positive or negative news at the time the information is tipped. To make sure I do not create a forward-looking bias in trading returns, I base this distinction on information available to the inside traders at the time they trade by using long positions and call options to indicate positive news and short positions and put options to indicate negative news.[3] Almost all M&A announcements are positive news events (234 vs. 5). Earnings events are more evenly split between positive and negative news, with 66 positive events and 54 negative events. Clinical trials tend to be positive news events with 24 positive events compared to 13 negative events. The sale of securities is overwhelming bad news in the sample with 34 negative events and one positive event. In 18 cases, the details provided in the SEC complaints do not provide enough detail to classify an event as positive or negative, including the 12 cases in which the events themselves are not specified. A detailed breakdown of the types of events is presented in Internet Appendix Table 1.

3.2. Stock returns from insider trading

Panel B of Table 1 presents average stock returns for each event type. The stock returns are calculated as the return from buying stock on the first trading date after the original tipper first receives the information through the date of the corporate event. If the date that the original source receives the information is not available in the filing documents, I use the first date that the original source tips the information. Panel C presents averages of the number of days over which event returns are measured. Not all tippees earn returns equal to those in Table 1 because many tippees do not receive the information until closer to the event date and some do not trade stock. The final column of Table 1 aggregates stock returns by taking the average of the returns for a long position in positive events and a short position in negative events.

Stock returns from insider trading are large by any measure: on average, trading on inside information earns re-

[2] The ethnic origins are African, Anglo-Saxon, Baltic, Celtic, East Asian and Pacific, European-Other Eastern, European-Other Western, Hispanic, Japanese, Jewish, Muslim, Nordic, South Asian, and Unclassified. The ethnicity groupings reflect the multidimensional view that defines ethnicity based on kinship, religion, language, shared territory, nationality, and physical appearance (Mateos, 2007).

[3] There are no instances in the data of different inside traders taking opposing positions for the same event.

Table 1
Corporate events and returns.
This table presents statistics for 465 corporate events in which the SEC or DOJ identified illegal insider trading, over the years 1996–2013. Panel A reports the number of occurrences of an event type. Panel B reports the average raw stock return from the date that the original tipper receives the information through the announcement date of the event. Panel C reports the average number of trading days over the same time period. Panel D reports the average raw stock return on the announcement date of the event. Negative and Positive columns indicate the expected effect on stock prices, based on the trading behavior of tippees. All includes 18 events that cannot be classified as positive or negative. Stock returns in the All column are calculated as long positive events and short negative events.

		Outcome	
Event type	All	Positive	Negative
Panel A: Frequency of events			
Clinical trial/drug regulation	37	24	13
Earnings	123	66	54
M&A	239	234	5
Operations	13	8	3
Sale of securities	35	1	34
Other	18	2	3
Total	465	335	112

	All		Positive		Negative	
	Mean	Median	Mean	Median	Mean	Median
Panel B: Information to event returns (%)						
Clinical trial/drug regulation	79.7	37.1	101.2	36.8	−38.6	−41.7
Earnings	13.5	10.2	14.7	10.4	−12.2	−10.2
M&A	43.1	35.5	43.7	35.7	−20.3	−17.9
Operations	24.9	18.9	22.9	22.2	−29.7	−12.9
Sale of securities	12.8	12.4			−12.8	−12.4
Other	8.9	0.0	−4.8	−4.8	−28.9	−28.9
Total	34.9	23.3	42.4	29.6	−16.8	−12.7
Panel C: Information to event time (trading days)						
Clinical trial/drug regulation	9.2	8.5	11.2	10.0	5.3	3.0
Earnings	11.3	7.0	12.3	8.5	10.2	5.3
M&A	30.5	16.0	31.1	16.5	7.8	4.0
Operations	6.1	3.0	7.9	4.0	2.0	2.0
Sale of securities	10.9	8.0	5.0	5.0	11.1	8.0
Other	44.3	4.0	3.0	3.0	101.1	15.3
Total	21.3	10.0	25.0	11.0	12.2	7.0
Panel D: Announcement day returns (%)						
Clinical trial/drug regulation	50.0	32.3	52.4	9.3	−45.4	−43.3
Earnings	9.2	7.0	7.9	6.0	−10.7	−11.4
M&A	21.9	11.0	22.3	11.3	−6.7	−6.9
Operations	16.9	7.1	12.1	3.2	−28.0	−10.0
Sale of securities	0.2	−0.8			−0.2	0.8
Other	4.4	0.0	−2.7	−2.7	−11.2	−11.2
Total	18.9	7.1	21.8	8.5	−12.0	−5.8

turns of 34.9% over 21.3 trading days. Because the returns are based on idiosyncratic inside information, the trades bear virtually no financial risk, though there is legal risk. Clinical trial and drug regulatory announcements generate the largest returns, on average, with gains of 101.2% for positive events and −38.6% for negative events, with an average holding period of just 9.2 days. M&As generate average returns of 43.1% in 30.5 days. Insider trading based on earnings announcements generates relatively smaller returns of 13.5% in 11.3 days. Also, median trading periods are small: 16 days for M&A events and ten days for all types of events.

As a comparison, Panel D of Table 1 presents the one-day raw return on the announcement of the event. For nearly every type of event, inside traders' investments (positive or negative) correctly predict the direction of the average stock returns on the announcement date. In addition, comparing the announcement day returns (Panel D) to the total returns (Panel B) reveals that announcement returns are substantially lower than the inside trader returns (the difference is statistically significant, with a t-statistic of 7.7). This means that a substantial fraction of the total return is realized in the run-up period. Across all event types, the run-up accounts for 49% of the total return when the news is positive. Consistent with short sale constraints, the run-up only accounts for 28% of the total return when the news is negative.

3.3. Firms

Table 2 presents summary statistics of the firms at the event level. The sample includes 351 firms whose stocks are traded by inside traders and whose data are available on the Center for Research in Security Prices (CRSP)-Compustat merged database. The missing observations tend to be small firms or foreign firms, primarily

Table 2
Event firms summary statistics.
This table presents summary statistics of the firms whose stocks are illegally traded based on inside information, using data from 465 corporate events over the years 1996–2013 in which the SEC or DOJ identified illegal insider trading. Total dollars invested by tippees is the total dollar amount of a company's stock purchased or sold across all trades by all inside traders in the data. Daily invested/daily dollar volume is the average daily dollars invested by tippees divided by daily dollar volume.

				Percentiles				
	Mean	S.D.	Min	25th	50th	75th	Max	Observations
Market equity (billions)	10.09	37.39	0.01	0.30	1.01	3.56	422.64	391
Employees (thousands)	13.71	41.63	0.00	0.37	1.70	6.55	398.46	387
Tobin's Q	2.54	2.41	0.35	1.31	1.87	3.06	36.24	391
Daily trading volume (millions)	3.18	8.85	0.00	0.21	0.68	1.85	71.98	393
Daily dollar trading volume (millions)	114.32	372.91	0.02	2.64	13.08	47.19	3456.96	393
Total dollars invested by tippees (millions)	4.06	12.99	0.01	0.08	0.37	1.43	132.64	269
Daily invested/daily dollar volume (%)	4.66	12.48	0.00	0.09	0.63	3.71	95.44	243

Chinese, which are traded on over-the-counter (OTC) markets. Because there are 465 events, many of the firms have information tipped about multiple events. For instance, Best Buy Co. has five different earnings announcements in the sample.

The firms in the sample are relatively large, though they vary widely. The average firm's market equity is $10 billion and the median firm's market equity is $1 billion. As a comparison, the median firm listed on the New York Stock Exchange (NYSE) in December 2011 has a market equity of $1.2 billion. These statistics suggest that the median sample firm is roughly the same size as the median firm listed on the NYSE.

The dollar trading volume of larger firms may be attractive for illegal inside traders because they are less likely to affect the stock price through their trades. The median firm has a daily trading volume of about 680,000 shares and a daily dollar trading volume of $13.08 million. To compare the normal trading volume of the sample firms to the illegal trading volume, I first aggregate the total dollars invested by inside traders over all the days in the period between when the original source receives the information and the event date. The total amount traded by tippees is $370,000 for the median event and $4.06 million for the average. I next calculate the average daily dollar amount of illegal trades divided by the firm's average daily dollar volume during a non-event period. The ratio is 0.63% at the median and 4.66% at the mean. At the 75th percentile, the ratio is 3.71%, a significant fraction of the daily volume.

Compared to all firms in the CRSP database, the sample of industries represented in the illegal trading database overweights high-tech industries. Using industry distributions for firms in CRSP may be an inaccurate benchmark because a large fraction of the sample involves trading around mergers, which tend to cluster by industry. Using a sample of public, US merger targets from 2004 to 2012 from Securities Data Company (SDC) as a benchmark, I still find that the sample overweights high-tech industries. See Internet Appendix Table 2 for details.

4. Who are inside traders?

Prior research shows that trading behavior varies by an individual's characteristics, such as age (Korniotis and Kumar, 2011), gender (Barber and Odean, 2001), wealth (Calvet, Campbell and Sodini, 2009), occupation (Dhar and Zhu, 2006), and geographic location (Massa and Simonov, 2006). These same characteristics could also be related to insider trading behavior. In this section, I provide a demographic profile of inside traders and describe summary statistics of their trading behavior.

4.1. Demographic profile

Table 3 presents summary statistics of the people in the sample, constrained by data availability. Of the 622 people in the sample, 162 people are tippers only, 249 are tippees only, 152 are both tippees and tippers, and 59 are original information sources who do not tip anyone else. Securities were traded by 399 people. The average person gives 1.5 tips, which equals the number of tips received by the average person since every tip is received by someone else in the sample. In unreported statistics, of those who only share tips, the average number of tips shared is 2.36. Of those who only receive tips, the average number of tips received is 1.96. Of those who both give and receive tips, the average person receives 2.99 tips and gives 3.68 tips.

Korniotis and Kumar (2011) show that older investors have greater investment knowledge and Barber and Odean (2001) show that women are less likely to trade than men. Across my entire sample of inside traders, the average age is 44.1 years, the youngest person is 19 years old, and the oldest is 80. Thus, inside traders' ages vary significantly. In contrast, there is a large imbalance in the gender of inside traders, with just 9.8% women in the sample. This may reflect that women are less likely to trade than men, but it could also reflect that women are less likely to receive information or to be named in an investigation.

Second, a person's occupation might influence his chance of receiving and sharing inside information. For example, corporate executives have access to inside information and professional investors have a need for inside information. Table 4 presents summary statistics of inside traders by nine types of occupations. Unsurprisingly, the most common occupation among inside traders is top executive with 107 people. Of these, 24 are board members and the rest are officers. However, the sample also includes other types of occupations: 55 mid-level corporate managers and 59 lower-level employees, including eight secretaries, 11 information technology specialists, and a few nurses, waiters, and a kindergarten teacher. There are 61 people who work in the "sell-side" of Wall Street

Table 3
Summary statistics of people involved in insider trading.
This table presents summary statistics for the 622 people in the sample of insider trading from 1996 to 2013. Data are from SEC and DOJ case documents, plus additional sources detailed in the paper. Median house value (Median house size) is the median estimated value (square footage) over all properties owned by a person that are also listed as a person's residence in the LexisNexis data. Home values and square footage are as of September 2014 from Zillow. Tips given is the number of insider trading tips given to others. Tips received are the number of insider tips received. Total invested is the aggregated dollar amount of all trading positions in absolute value. Thus, this includes the size of short positions. Total gains are the aggregated dollar amount received by a person across all events and trades. Average return is the average of a person's trades, based on actual buy and sell dates from the SEC and DOJ documents.

				Percentiles				
	Mean	S.D.	Min	25th	50th	75th	Max	Observations
Panel A: Demographics								
Age	44.1	11.5	19.0	35.8	42.7	51.5	80.0	454
Female (%)	9.8	29.8	0.0	0.0	0.0	0.0	100.0	498
Median house value ($1,000s)	1114.3	1846.5	49.6	390.0	656.3	1170.5	25600.0	365
Median house size (100 ft.^{2})	30.0	21.3	7.5	18.6	26.5	35.4	316.4	351
Panel B: Information sharing								
Tips given	1.5	3.2	0.0	0.0	1.0	1.0	29.0	622
Tips received	1.5	2.5	0.0	0.0	1.0	1.0	24.0	622
Panel C: Trading								
Ever traded stock	82.5	38.1	0.0	100.0	100.0	100.0	100.0	399
Ever traded options	38.8	48.8	0.0	0.0	0.0	100.0	100.0	399
Total invested ($1,000s)	4288.0	25334.9	4.4	74.5	226.0	1116.2	375317.3	255
Average invested per tip ($1,000s)	1690.3	6088.6	4.4	65.0	200.0	701.4	72427.5	255
Total invested/median house value (%)	581.6	3609.5	0.6	13.2	38.9	140.3	44183.1	159
Total gains ($1,000s)	2331.6	13207.1	0.9	34.2	136.0	606.0	139500.0	399
Average gains per tip ($1,000s)	1289.9	10036.0	0.1	20.6	72.4	285.0	139000.0	399
Average return (%)	63.4	231.8	0.0	14.0	26.4	46.5	3347.3	255

Table 4
Summary statistics by occupation.
This table presents averages of age, gender, tipping activity, investment, and returns by occupation for the 622 people in the sample of insider trading from 1996 to 2013. Data are from SEC and DOJ case documents, plus additional sources detailed in the paper. Table 3 defines the variables. Internet Appendix Table 3 presents a breakdown of occupations into narrower categories.

Occupation	Count	Percent	Age	Female	House value ($1,000s)	Tips given	Tips received	Median invested per tip ($1,000s)	Median gains per tip ($1,000s)	Median return
Top executive	107	17.3	50.9	6.1	1,152	1.5	0.5	377	2,903	33.7
Corporate manager	55	8.9	41.3	5.6	624	1.6	0.6	1,973	286	71.8
Lower-level employee	59	9.5	41.5	25.5	621	1.7	1.5	558	149	47.5
Sell side/lawyer/accountants	61	9.9	41.7	11.1	1,164	3.0	1.9	3,756	255	58.8
Buy side: manager	60	9.7	42.6	6.4	3,006	1.4	2.6	5,972	5,768	37.0
Buy side: analyst/trader	65	10.5	35.5	5.2	1,061	2.7	3.1	2,051	442	117.7
Small business owner	39	6.3	47.4	5.3	678	0.9	2.3	204	196	62.0
Specialized occupation	38	6.1	52.0	2.8	729	1.2	1.6	599	234	32.8
Unknown	135	21.8	41.5	20.4	613	0.5	1.1	584	355	77.0

including 13 accountants, 24 attorneys, four investment bankers, and three sell-side analysts. Consistent with a desire to obtain inside information, a large fraction of the sample are "buy-side" investors. There are 60 portfolio and hedge fund managers and 65 lower-level buy-side analysts and traders. Small business owners and real estate professionals account for 39 people in the sample and 38 people have specialized occupations, including 16 consultants, 13 doctors, and nine engineers. For 135 people, I cannot identify an occupation. Internet Appendix Table 3 provides a more detailed breakdown of occupations.

Next, an insider's wealth could influence how he trades and shares information. Wealthier individuals have more resources to invest on inside information, but they also have more to lose if they are caught. I use an inside trader's home value as an imperfect proxy for wealth. Because identifying the specific timing of real estate purchases is difficult in the LNPRD, for each inside trader, I compute his median house value across all of the real estate he owned at any time. I restrict real estate holdings to those that are listed both as real property and as a residence in the LNPRD to filter out investment properties. The average inside trader's home is worth an estimated $1.1 million in September 2014, with a median of $656,300. According to data from the National Association of Realtors, the national median sales price of single-family homes at the same time is $212,400, which is less than the 25th percentile of inside traders' home values. In unreported tests, I find that the values of 75% of inside traders' homes are greater than the median home value in the inside traders' zip codes. Similarly, the value of the average inside trader's house is worth 1.9 times the median house in the same zip code. Thus, inside traders tend to own expensive houses in expensive neighborhoods.

Finally, geographic location might affect who gets tipped inside information. Inside traders likely work at a corporate headquarters or a financial center, such as New York. However, information might then spread widely through social connections. I find that inside traders are located all across the country, including both urban and rural locations. However, based on either state-level population, aggregate income, or the population of people invested in the stock market (using participation rates from the Health and Retirement Study), the sample of inside traders is overweighted in California, New York, and Florida, and underweighted in Texas, Ohio, and Virginia. The sample also includes inside traders located in other countries, including Brazil, China, Canada, Israel, and Thailand. See Internet Appendix Fig. 1 for details.

4.2. Trading behavior

The total amount invested per trader ranges from a minimum of $4,400 up to a maximum of $375 million invested by Raj Rajaratnam, the founder of the Galleon Group hedge fund. For most cases, total profit or losses avoided are reported in the SEC filings. In contrast, total invested is not always reported, which limits the sample. In some cases, I can infer total invested by using information on number of shares or options traded reported in the filings. The average total amount invested is $4.3 million and the median amount is $226,000. The median amount invested per event is $200,000, with an average of $1.7 million. These large amounts are explained in part by the composition of the types of people that receive inside information, including portfolio managers who invest their funds' assets, not their personal assets. In addition, many of the SEC complaints document that inside traders sell all of the existing assets in their individual portfolios and borrow money to concentrate their holdings in the insider trading firm. As evidence, the median inside trader invests an amount worth 39% of his median home value.

Across all tips, the median investor realizes a total gain of $136,000 in ill-gotten profits and losses avoided. The average investor realizes gains of $2.3 million. Per tip, the median investor gains $72,400. The average percentage return for inside traders is 63.4% and the median is 26.4%. These returns are higher than the average event returns presented in Table 1 because of the use of options. Of all people that traded securities, 83% traded stock and 39% traded options at least once. Other securities are traded in a tiny minority of tips, including spread bets, mutual funds, employee stock options, contracts-for-difference, and credit default swap (CDS) contracts.

Of those that invest, buy-side managers invest the largest amount per tip (median of $6 million), followed by people who work in the sell-side ($3.8 million) and buy-side analysts ($2 million). Small business owners invest the least with a median investment of $203,900 per tip. It is interesting to note that the median mid-level manager invests more than the median top executive ($2 million compared to $376,800). This likely represents the higher scrutiny on the investments of top executives. Buy-side analysts have the highest median return of 117.7%. Buy-side managers have median returns of 37%, among the lowest returns across occupations. However, buy-side managers earn the highest dollar gains for their trades at $5.8 million per tip, at the median.

Table 5
Tippers and tippees social relationships.
This table reports the frequency of different types of social relationships among the 461 pairs of people in the insider trading data. When one person tips insider information to another person, they are considered a pair. Pairs can have more than one type of social relationship, so the sum of relationship types is greater than 445. The type of relationship is defined based on the text in SEC and DOJ case documents. Business associates are people who work together or know each other through business relationships where neither person has a supervisory role over the other. Boss refers to business relationships where one person is subordinate to another. Client is a relationship where one person is business client of the other. Data are from SEC and DOJ illegal insider trading case documents filed between 2009 and 2013.

Type of relationship	Count	Fraction of all pairs	Fraction of relationship type
Family	104	22.6	
Dating/engaged	7	1.5	6.7
Married	15	3.3	14.4
Parent-child	20	4.3	19.2
Siblings	25	5.4	24.0
In-laws	12	2.6	11.5
Other	9	2.0	8.7
Unspecified	16	3.5	15.4
Business	160	34.7	
Business associates	87	18.9	54.4
Boss	41	8.9	25.6
Client	32	6.9	20.0
Friends	162	35.1	
Acquaintances	3	0.7	1.9
Friends	115	24.9	71.0
Close friends	44	9.5	27.2
No social relation listed	98	21.3	

5. How are inside traders connected to each other?

Inside traders have an incentive to share information with people they trust. Thus, strong social networks are expected to underlie the spread of information in insider trading networks. To test this hypothesis, I investigate the closeness of inside traders in a few ways. First, I measure closeness using the direct observations of social relationships reported in the case filings. Then, I measure closeness using indirect measures, including geographic proximity and shared attributes.

5.1. Social relationships

Table 5 presents the prevalence of information flows by the type of relationship between the 461 pairs of tippers and tippees in the sample. Of these relationships, 23% are familial, 35% are business-related, 35% are friendships, and 21% do not have any clear relationships. Multiple types of relationships are allowed. In unreported numbers, 11 pairs of inside traders have both familial and business relationships, 56 pairs of relationships are both business-related and friendships, and four relationships are both family and friends (typically in-laws and distant family members).

The family relationships are led by siblings (24% of familial relationships) and parent-child (19%). About 14% of the family relations are between married couples and 12% are through in-law relationships. The 'other' category, which includes cousins, uncles, aunts, etc., accounts for 9% of family relations. The 'unspecified' category (15% of family relationships) includes observations where the SEC and DOJ filings indicate that people are relatives, but don't specify the exact relationship.

Among the business-related relationships, 54% are among associates. Business associates are people that work together or know each other through their profession. In comparison, boss-subordinate relationships account for 26% of business-related ties and client-provider relationships account for 20%. This means that slightly more than half of business-related relationships are between people of equal status, and half are relationships where one person holds a supervisory role over the other.

For friendship relations, the filings commonly describe relationships as either friends or close friends, and occasionally as acquaintances. In the sample, just three pairs are described as acquaintances, compared to 115 described as friends, and 44 described as close friends.

The 98 pairs in Table 5 in which no social relationship is listed comprise a sizable number of expert networking firm relationships, where inside traders are paid consultants to clients of the expert networking firm. Of the 98 pairs, 22 are related to the expert network firm Primary Global Research LLC (PGR). Expert networking firms provide industry experts that work as paid consultants to investment managers. However, in the case of PGR, the consultants provided illegal insider trading tips. Thus, the relationships between PGR consultants and investment managers are not just missing observations. Instead, these pairs actually have no social relationships other than sharing inside information.

5.2. Geographic proximity in relationships

Close geographic proximity facilitates social interaction, even with advances in electronic communication (Goldenberg and Levy, 2009). In the context of insider trading, greater social interaction could reduce uncertainty in a relationship and increase trust between a tipper and a tippee. Therefore, I expect that inside traders are more likely to share information with people that live close by than with people that live far away. This prediction is the key assumption in Brown, Ivković, Smith and Weisbenner (2008). They find that stock market participation is greater when other members of a community are stock market investors and when the community is more sociable. They infer that this correlation is caused by social interactions among people who live in close proximity, though they cannot observe social interactions directly. In contrast, my setting allows me to directly observe whether inside traders are more likely to share information with people who live close by.

Table 6 presents summary statistics of the geographic distance between inside traders. Distance is calculated as the great circle distance in miles between the cities of the people in a pair. Longitude and latitude for each city are taken from Google Maps. Therefore, if two people live in the same city, they have a distance of zero miles.

Consistent with my hypothesis, inside traders live close to each other. Across all pairs of inside traders, the median distance is 26.2 miles, with an average of 581.1 miles. The maximum distance is from Hong Kong to Schwenksville, Pennsylvania at 8,065 miles. At the median, the geographically closest relationships are familial relations, with a median of 14.3 miles, followed by business-related relationships with a median of 18.9 miles, and friendship relationships at 28.4 miles. If no social relation is listed, the members of a pair are located substantially farther from each other, at 80.9 miles at the median, though still relatively close. In unreported tests, I find no statistically

Table 6
Geographic distance by relationship.
Geographic distance is measured in miles using the great circle distance between the cities of residence of the people in a pair. Residences are from the SEC and DOJ case documents. Acquaintances and unknown family relations are omitted because they have very few observations. Table 5 provides a description of the sample.

	Mean	S.D.	Min	Percentiles			Max	Observations
				25th	50th	75th		
All	581.1	1190.8	0	0.0	26.2	739.3	8065.9	229
Family	466.3	1080.1	0	0.0	14.3	322.5	5350.4	59
Married/dating	47.3	183.4	0	0.0	0.0	0.0	710.2	15
Parent-child	326.8	603.6	0	14.3	26.2	160.1	1986.5	13
Siblings	783.3	1490.8	0	6.2	28.0	1063.6	5350.4	14
In-laws	1110.5	1751.5	0	9.6	216.5	1626.3	5350.4	9
Other	88.0	128.3	0	8.1	11.5	237.3	307.6	7
Business ties	327.5	709.5	0	3.5	18.9	219.9	4452.0	98
Associates	334.5	751.6	0	0.0	16.8	236.8	4452.0	57
Boss	198.4	395.1	0	3.9	24.8	53.4	1235.4	22
Client	455.9	857.2	0	10.7	19.0	625.6	2666.9	19
Friendship	715.1	1352.4	0	4.0	28.4	1045.8	8065.9	106
Friends	708.2	1247.7	0	4.5	32.1	1077.6	6622.1	72
Close friends	694.6	1581.8	0	0.0	26.2	835.3	8065.9	32
No social relation listed	962.2	1680.0	0	15.0	80.9	1117.4	5358.7	14

significant difference in the medians of family, business, or friendship relationships. These statistics suggest that relatively small geographic zones are reasonable proxies for a large fraction of information flows, across all types of interpersonal relationships, as assumed in prior research (e.g., Brown, Ivković, Smith and Weisbenner, 2008).

5.3. Shared attributes of inside traders

Sociologists have shown that people in social relationships tend to have similar socio-demographic attributes (McPherson, Smith-Lovin and Cook, 2001). For instance, Smith, McPherson and Smith-Lovin (2014) provide evidence that people in the same social network tend to have the same gender, race, religion, age, and education. Guiso, Sapienza and Zingales (2009) show that similarity in language and ancestry is related to greater trust. Therefore, I expect that inside traders will share common socio-demographic attributes given the importance of trust in inside trading networks.

First, I test whether tippers and tippees share common educational backgrounds (Cohen, Frazzini and Malloy, 2008). In 51 pairs, the filings provide the time when the individuals first met: before college, during college, in graduate school, or after completing school. To these 51 pairs, I append 69 pairs of family relations in which I can assume the traders knew each other before college.[4] I also assume that the 22 pairs of inside traders connected through PGR met after completing school.

For the 142 pairs of inside traders with available data, 64% met before college, 10% met in college, 6% met in graduate school, and 20% met after completing school. Excluding family members, 29% met before college, 20% met in college, 11% met in graduate school, and 40% met after completing school. These patterns imply that people who share inside information have long-standing and close relations with each other. It also implies that the presence of school-ties is related to actual social interactions, as assumed in a number of papers (e.g., Cohen, Frazzini and Malloy, 2008; 2010), though information is mostly shared between people who met before college, once family relations are included.

Next, Fig. 2 provides a heat map of the connections between tippers and tippees by occupation. These relations are based on binary connections between people, where a cell entry reports the total number of pairs where the tipper occupation is listed on the row heading and the tippee occupation is listed on the column heading. Unknown occupations are not detailed in the figure, but they are included in the totals for each row and column.

The heat map provides an indication of the direction of information flow. Top executives are by far, the most frequent tippers. Their tippees are spread over all occupations. Top executives tip other top executives (15% of top executive pairs), specialized occupations like doctors and engineers (13%), buy-side analysts (10%), and managers

Tippees

Tippers	Top executives	Corporate managers	Lower-level employees	Sell side	Buy side: managers	Buy side: analysts	Small business owners	Specialized occupations	Total
Top executives	15	6	7	5	11	10	9	13	100
Corporate managers	6	5	2	2	10	9	3	1	44
Lower-level employees	3	2	8	1	5	2	10	5	45
Sell side	1	1	4	13	3	14	8	1	51
Buy side: managers	1	2	3	0	24	8	0	0	44
Buy side: analysts	4	0	6	0	19	31	2	2	90
Small business owners	1	0	3	4	1	2	3	1	29
Specialized occupations	1	0	0	2	8	1	2	2	21
Total	35	17	38	39	85	86	41	29	473

Fig. 2. Number of connections between tippers and tippees by occupation. This figure shows the number of tipper–tippee pairs sorted by the occupation of the tipper and the tippee. Darker colors represent more pairs. Totals include connections to people with unknown occupations, so row and column sums do not add up to the totals. Data are from 622 people in the sample of illegal insider trading from 1996 to 2013. Occupation definitions are detailed in Internet Appendix Table 3. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

(11%), and all other occupation categories in the sample. In contrast, buy-side analysts are the next most common tippers with 90 pairs, but their tippees are concentrated among other buy-side analysts (34% of their tippees) and buy-side managers (21%). Comparing the number of pairs in which a particular occupation is a tippee compared to a tipper, top executives are 2.85 times more likely to be a tipper than a tippee. In contrast, buy-side managers are tippees roughly twice as often as they are tippers.

Fig. 3 presents a similar analysis by age. The strong diagonal component of the figure reveals that tippers and their tippees tend to be close in age, as predicted. The eight groups where tippers and tippees are the same age account for 35% of all pairs, compared to 12.5% if pairs were randomly distributed. In the off-diagonal regions, substantially more relationships include younger tippers sharing information with older tippees than vice versa (108 pairs versus 79 pairs).

Fig. 4 presents the prevalence of pairs by surname ancestry. As before, the strong diagonal in the figure reveals that people are more likely to tip other people who share the same surname ancestry. For example, of the sample of tippers with South Asian surnames, one-third of the tippees also have South Asian surnames, out of nine possible ancestries. Similarly, of tippers with Muslim surnames, about half of their tippees also have Muslim surnames. In unreported tests that exclude family relationships, a similar though weaker pattern emerges where tippers and tippees share a common surname ancestry. These results are consistent with the importance of shared backgrounds for insider trading networks.

[4] The data do not provide information on when in-laws, engaged, and married couples met, so I exclude them from the calculation. One pair of "other" family relations met before college, so I do not double-count this observation when I calculate 69 remaining family pairs.

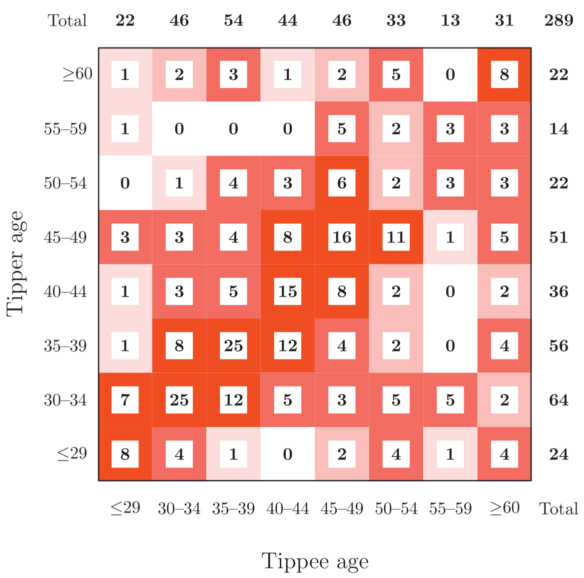

Fig. 3. Number of connections between tippers and tippees by age. This figure shows the number of tipper–tippee pairs sorted by the ages of the tipper and the tippee. Darker colors represent more pairs. Data are from 622 people in the sample of illegal insider trading from 1996 to 2013. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

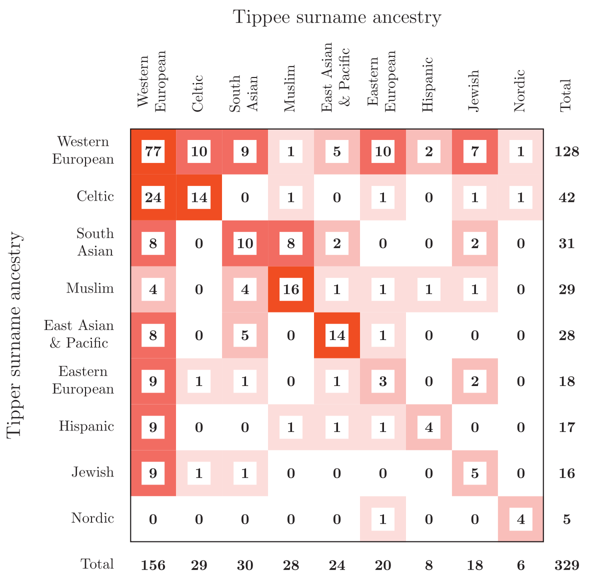

Fig. 4. Number of connections between tippers and tippees by ancestry of surname. This figure shows the number of tipper–tippee pairs sorted by the ancestries of the tipper and the tippee. Darker colors represent more pairs. Totals include connections to people with unknown ancestries, so row and column sums do not add up to the totals. Data are from 622 people in the sample of illegal insider trading from 1996 to 2013. Ancestry of surnames is from the Onomap database. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

Finally, in unreported statistics, I find that subordinates are more likely to tip supervisors than vice versa. In 63% of boss-subordinate relationships the tipper is the subordinate, a significant difference from 50%. Similarly, in parent-child relationships, the tipper is the parent in 30% of cases, statistically less than 50%. These results show that inside traders might share information in an attempt to please higher status individuals, such as employers and parents.

5.4. Counterfactual observations to analyze who gets tipped and who doesn't

The above results show that information flows across strong social relationships, as predicted. However, because all of the people in the sample received inside information at some point, I cannot compare the strength of their social relationships with people who could have received a tip, but did not. It is possible that the people who did not receive a tip have even stronger social relationships to the tipper. In this section, I construct a counterfactual sample of potential tippees to better understand how tippers choose among potential tippees when sharing inside information.

For each inside trader in the data that I can identify in the LNPRD, I record the family and personal associates listed in the LNPRD, as described above. Then I append to this set any insider traders in the SEC and DOJ documents that do not appear in the list of a tipper's family and associates. From this broader set of social relations, I create a dummy variable equal to one for each person that receives inside information from the tipper.

Table 7 provides logit regression tests on the likelihood of receiving a tip. Columns 1 and 2 include gender, age, and the type of social relationship as explanatory variables. Columns 3 and 4 include tipper fixed effects to account for all observable and unobservable characteristics that could influence with whom a tipper chooses to share information.

Across all specifications, I find that potential tippees that are close in age and are of the same gender as the tipper are more likely to receive inside information. Family members are less likely to be tipped than are associates. However, compared to non-family associates, husbands are more likely to be tipped, while wives, sisters, and in-laws are less likely to be tipped. Brothers and fathers are equally likely to be tipped as associates. These results suggest that information flows among family and friends in specific patterns.

To my knowledge, in the literature on social networks in finance, this analysis is the first to provide a counterfactual sample of connections. The LNPRD offers a unique opportunity to observe social networks for virtually any person in the US. However, I acknowledge that the data are limited. First, the list of potential tippees that I record from LNPRD is not exhaustive. Family members are limited to ten people and associates are only identified through records available to LexisNexis. However, if anything, the LNPRD will be biased towards finding closer relatives and associates, which likely makes it harder to find any distinction between actual and potential tippees. Second, it is likely that a tipper shares information with other people

Table 7
The likelihood of receiving a tip using potential tippees.
This table presents logit regression coefficients where the dependent variable equals one if a person receives an insider trading tip and zero otherwise. Observations include a tipper's family members and person associates. Family members and person associates are identified using the LexisNexis database. Person associates are non-family members who have a connection to the tipper. Columns 3 and 4 include tipper fixed effects. In columns 2 and 4, the omitted benchmark category is person associates, which means the coefficients on the family members are relative to the likelihood that a person associate receives a tip. Other are family members other than immediate family and in-laws, such as uncles and grandparents. Standard errors are clustered at the tipper level. Table 5 provides a description of the sample. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

	Likelihood of receiving a tip			
	(1)	(2)	(3)	(4)
Same gender	1.447***	1.351***	1.223***	1.155***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Age difference	−0.049***	−0.063***	−0.049***	−0.062***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Family member	−1.097***		−0.618***	
	(<0.001)		(<0.001)	
Omitted baseline category: Person associates				
Husband		1.651***		1.862***
		(0.007)		(<0.001)
Wife		−1.862***		−1.513**
		(0.003)		(0.017)
Brother		−0.435		−0.111
		(0.128)		(0.704)
Sister		−2.820***		−2.407**
		(0.007)		(0.018)
Father		−0.024		0.652
		(0.957)		(0.157)
Mother		−1.057		−0.387
		(0.171)		(0.615)
Son		0.468		0.698
		(0.433)		(0.183)
Daughter		−0.300		−0.223
		(0.781)		(0.831)
Other		0.644		0.987**
		(0.205)		(0.042)
In-law		−1.588***		−1.070***
		(<0.001)		(0.003)
Unknown		−3.907***		−3.569***
		(<0.001)		(<0.001)
Tipper fixed effects	No	No	Yes	Yes
Pseudo R^2	0.187	0.252	0.099	0.150
Observations	2,604	2,604	2,604	2,604

than just those named in the legal documents. These people may appear on the list of potential tippees from the LNPRD, but I would not correctly identify them as an actual tippee. For instance, mothers, sisters, and in-laws may receive information but either not trade or not get caught.

6. How does information diffuse across inside traders?

In this section of the paper, I trace out the path through which information flows from the original source to the final tippee. This provides a better understanding of how information flows across market participants and also how social relationships change as information diffuses. As information moves away from the original source, it loses value. The more people that have the information, the less valuable it becomes because stock prices will begin to incorporate the information. When inside information is more valuable, tippers are likely to share the information with closer contacts. As it loses value, tippers are likely to share the information more broadly. Thus, as information diffuses away from the original source, the social relationships between tippers and tippees are likely to become more distant. This hypothesis is consistent with the model in Stein (2008) which predicts that more valuable information remains more local.

To understand how information transmits away from the original sources through social networks, I identify "tip chains." An inside trader's order in the tip chain is the number of links he is removed from the original source. The first order in the tip chain is the connection between the original source and his tippees. If a tipper tips multiple tippees, then each of these tippees is in the same order in the tip chain.

Table 8 shows that as information progresses across the tip chain, a number of patterns emerge. The tippers that are in the first link in the tip chain are the original sources. They tend to be corporate insiders and sell-side professionals.[5] As the information transmits away from the original sources, officers become less common tippers, going from 34% of all tippees in the first link to 0% of tippers in fourth

[5] Internet Appendix Tables 4 and 5 provide a detailed breakdown of the identities of the original sources by type of event and by internal and external employees.

Table 8
Characteristics by order in tip chain.
This table presents the characteristics of tippers and tippees for each link in a tip chain. The order in a tip chain is the distance from the original source of the inside information, where distance is measured as information links between people. Tables 3 and 5 provide descriptions of the sample.

	Order in tip chain			
	1	2	3	≥ 4
Panel A: Tipper occupation				
Top executive	34.0	6.6	0.8	0.0
Corporate manager	13.7	8.6	3.1	0.0
Lower-level employee	16.1	5.2	11.5	3.6
Sell side/lawyer/accountants	26.3	6.9	29.8	7.3
Buy side: manager	1.0	15.2	17.6	12.7
Buy side: analyst/trader	1.9	27.9	27.5	70.9
Small business owner	0.7	6.9	7.6	1.8
Specialized occupation	1.4	13.4	1.5	0.0
Unknown	4.8	9.3	0.8	3.6
Panel B: Tipper demographics				
Female	11.5	14.8	4.5	10.5
Age	42.8	41.4	35.7	34.4
Median house value ($1,000s)	811.7	840.1	758.5	1,072.0
Panel C: Connections				
Family connection	24.6	15.5	28.4	11.9
Friendship connection	42.4	35.2	36.6	18.6
Business connection	28.4	47.0	34.3	66.1
No connection	20.9	19.7	15.7	11.9
Geographic distance – median (miles)	15.8	40.2	46.9	0.0
Same house value quintile	49.6	36.2	15.2	20.0
Same surname ancestry	51.9	33.8	42.1	42.5
Panel D: Trading				
Amount invested – median ($1,000s)	200.4	250.1	280.1	492.7
Gross profit – median ($1,000s)	17.6	36.3	39.5	86.0
Tip return – average (%)	46.0	43.5	29.2	23.0
Tip return – median (%)	25.2	27.9	28.2	18.8
Use shares dummy (%)	50.8	56.2	77.1	76.4
Use options dummy (%)	27.0	23.4	16.8	21.8
Panel E: Timing				
Time lapse from information to tip (days)	12.1	9.2	5.0	0.4
Tip passed on same day as received (%)	46.5	62.7	49.5	92.1
Holding period - average (days)	13.9	16.8	11.3	9.1
Holding period - median (days)	5.2	7.0	4.0	5.0

and subsequent links. Corporate managers, lower-level employees, and people in specialized occupations follow similar decreasing patterns. In contrast, buy-side managers and analysts are increasingly the tippers as the information travels further from the source, accounting for 12.7% and 70.9% of all tippees in the fourth and later links. Consistent with the movement of information from corporate executives to buy-side managers, tippers become younger and wealthier as the information flows further from the original source.

The table reveals clear patterns of social connections over the tip chain. In the first link, tippers and tippees are primarily friends (42.4%) and family members (24.6%) and then steadily decline as the tip moves further from the source to 18.6% for friendship connections and 11.9% for family connections by the fourth and later links. In contrast, business connections grow in prevalence from 28.4% in the first link to 66.1% by the fourth and later links. Similarity in tipper and tippees' house values and surname ancestry also decline over the tip chain. These results suggest that original sources share information with their most trusted relations – family members – but once the information moves further from the original source, tippers become less discerning.[6]

Table 8 next documents trading behavior of the tippees by their position in the tip chain. The median amount invested rises monotonically from $200,400 for the first tippee to $492,700 for the fourth and subsequent tippees. Median profits rise as well from $17,600 to $86,000 per tip. However, trading returns decline over the tip chain, indicating that the information becomes less valuable as stock prices begin to reflect the information. The initial tippee earns returns of 46.0% on average and 25.2% at the median. By the fourth link, the returns have dropped to 23.0% for the average and 18.8% for the median. The drop in returns is partially caused by an increase in the use of shares rather than options over the tip chain. These patterns are consistent with information flowing to professional traders over the tip chain. These traders invest large amounts of money using shares, rather than options. In return, they earn lower percentage returns, but greater dollar returns.

Next, Table 8 shows that the average time between receiving information and sharing it with others decreases over the tip chain. The original source waits 12.1 days, on average, before tipping the information. At the second link in the chain, the delay is 9.2 days, followed by 5.0 days at the third link, and then 0.4 days for the fourth and higher links. The fraction of tippers who tip the same day that they receive information is 46.5% for the original source, increasing to 92.1% in the fourth and higher links. This delay means that the period between when the tippee receives the information and the event date declines over time, from an average of 13.9 trading days in the first link to 9.1 days in the later links. Thus, information travels with a delay which helps to explain why stock price run-ups occur gradually, not immediately.

7. The networks of inside traders

To complete the investigation of how social networks influence insider trading, I investigate the structure of inside trading networks. Of the 183 inside trader networks in the sample, 59 contain only one person. These are people who obtained inside information and did not tip anyone else. The remainder of the size distribution of the networks is as follows: 60 networks with two members, 18 networks with three members, 18 networks with four members, 11 networks with five or six members, 11 networks with seven to ten members, and six networks with more than ten members.

Fig. 5 presents the largest network in the sample, which centers on the expert networking firm, Primary Global Research (PGR) and hedge funds owned by SAC Capital. Though this network is an outlier in the sample, with 64 members, its size makes it an interesting illustration of the

[6] Internet Appendix Table 6 presents ordinary least squares (OLS) and ordered logit regression tests with similar results.

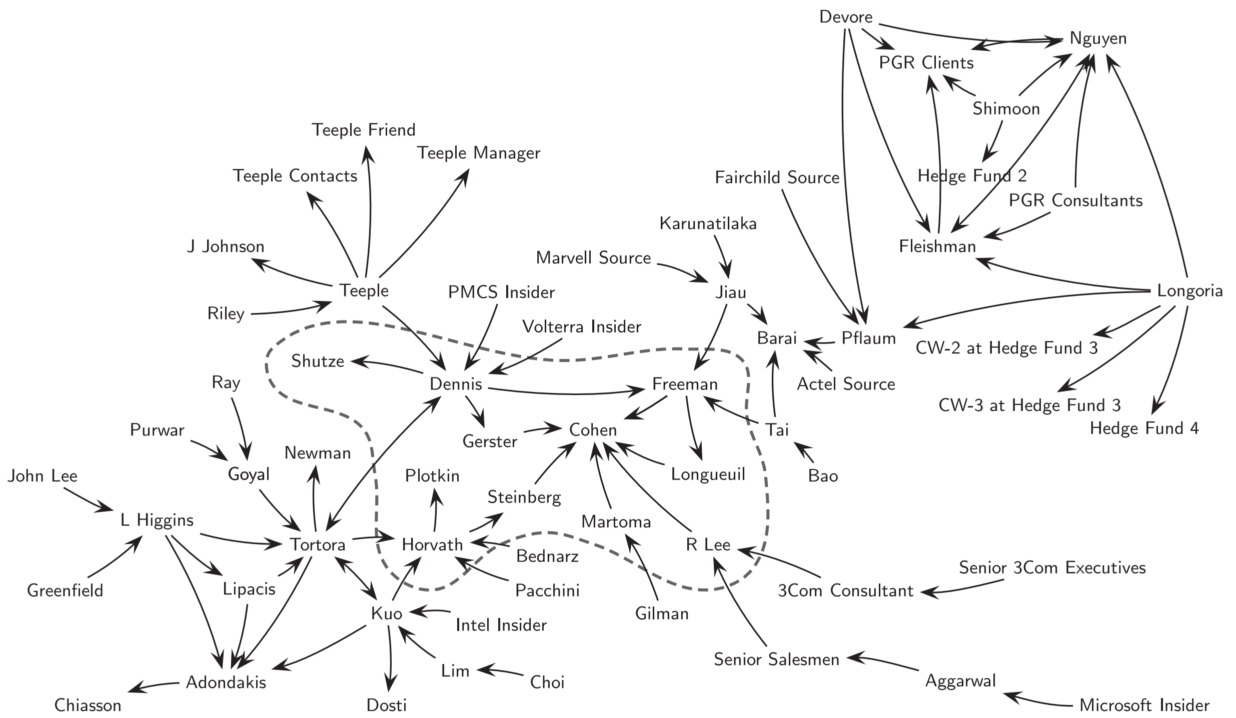

Fig. 5. SAC-PGR network. This figure represents the illegal insider trading network centered on the hedge funds controlled by SAC Capital and the expert networking firm, Primary Global Research. Arrows represent the direction of information flow. Insiders in the dashed region are affiliated with SAC Capital or its subsidiaries. Data are from SEC and DOJ case documents, plus additional source documents to identify individuals not named in the SEC and DOJ documents.

inside trader network of professional traders. Of the 64 inside traders in the network, 27 are affiliated with hedge funds.

PGR's business was to connect original sources of information with buy-side portfolio managers. The PGR employees in the network include Winnie Jiau, James Fleishman, Walter Shimoon, and Bob Nguyen, located at the top right of the network. Among other experts, they connected Daniel Devore and Mark Longoria, supply chain managers at Dell Inc. and Advanced Micro Devices, with various hedge fund managers. SAC Capital is connected to PGR through Winnie Jiau's tips to Noah Freeman, a portfolio manager at SAC. In addition to Freeman, the other ten inside traders within the dashed region in the figure are all affiliated with SAC Capital or its subsidiaries. Alec Shutze, Eric Gerster, Mathew Martoma, and Donald Longueuil were portfolio managers and Ronald Dennis was a tech analyst at the CR Intrinsic Investors unit of SAC. Gabriel Plotkin and Michael Steinberg were portfolio managers and Jon Horvath was a tech analyst at the Sigma Capital Management unit of SAC. Richard Lee was a portfolio manager at SAC's main unit. At the center of the network is Steven Cohen, the founder and principal of SAC Capital.

Cohen's centrality in the network reflects his centrality within SAC Capital. Cohen surrounded himself with his portfolio managers who collected information from various sources. Noah Freeman received information from Winnie Jiau. Mathew Martoma received information from Sidney Gilman, a medical doctor who oversaw clinical trials of a new drug. Steinberg and Gerster each received information from their analysts, Horvath and Dennis, who received information from a number of original and intermediate sources. Thus, Cohen received information from a wide variety of sources, but is not directly tied to any original source. In addition, Cohen never tipped anyone else. In comparison, Fig. 1 shows that Raj Rajaratnam had direct links to multiple original sources of information, including Rajat Gupta, a director at Goldman Sachs, Rajiv Goel, an executive at Intel, and Anil Kumar, a director at McKinsey & Company. Other large networks are presented as examples in Internet Appendix Figs. 2–4.

Table 9 presents summary statistics by the size of insider trading networks, starting with network characteristics. First, the density of a network is defined as the proportion of all potential connections that actually exist. If every node is connected to every other node, then the network is 100% dense. The table shows that as insider trading networks grow in size, they become less dense. For networks with six or more members, only 20% of possible information connections actually exist. Second, the diameter of a network is defined as the longest of all shortest paths between nodes in the network. Intuitively, diameter reflects the number of connections that separate the most distant nodes in a network. Table 9 shows that the average diameter increases as more members are added. This implies that additional members of an insider trading network are added at the periphery, rather than the center of a network. This provides additional evidence that networks become more dispersed and sprawling, instead of compact and closely tied to a central hub. Third, a node's

Table 9
Tipper and tippee characteristics by size of insider network.
This table reports characteristics of people in information networks of increasing size. Size of network refers to the number of people in an insider network (where every member can be reached by every other member through at least one path). Density is the proportion of all possible connections that actually exist. The diameter of a network is the longest of all shortest paths between any two members. Average cluster is the average node's clustering, where clustering is the fraction of a node's links that are also linked to each other. Tables 3 and 5 provide descriptions of the sample.

	Size of network			
	1	2	3–5	≥ 6
Panel A: Network characteristics				
Density		1.0	0.6	0.2
Diameter		1.0	2.3	4.4
Average cluster		2.0	0.2	0.1
Panel B: Personal characteristics				
Female tipper (%)	3.4	22.7	11.7	7.2
Female tippee (%)		8.6	10.6	8.5
Tipper age	47.8	45.4	43.6	42.1
Tippee age		44.9	44.5	42.3
Tippee house value – mean ($1,000s)		856.8	893.2	1311.6
Tippee house value – median ($1,000s)		594.8	476.2	768.0
Tipper house value – mean ($1,000s)	849.6	884.2	796.2	1548.4
Tipper house value – median ($1,000s)	572.7	560.7	620.6	960.8
Panel C: Social connections				
Family connections (%)		43.2	28.2	23.8
Business connections (%)		20.5	34.0	36.4
Friendship connections (%)		36.4	37.8	39.7
Geographic distance – mean (miles)		523.8	326.0	583.6
Geographic distance – median (miles)		7.2	33.6	36.6
Panel D: Trading				
Amount invested – mean ($1,000s)	725.3	1054.0	1227.7	2457.3
Amount invested – median ($1,000s)	131.6	294.8	154.9	303.1
Gross profit – mean ($1,000s)	2666.1	1248.1	255.7	526.6
Gross profit – median ($1,000s)	67.4	154.3	41.7	216.1
Tip return – mean (%)	137.7	82.0	51.0	37.3
Tip return – median (%)	32.4	34.8	34.2	28.0
Panel E: Timing				
Time lapse from information to tip (days)		11.3	15.4	9.3

clustering coefficient is the fraction of a node's links that are also linked to each other. The average clustering coefficient across nodes decreases as networks get larger. These network statistics reveal that as a network gets larger, it spreads out from its outer members like a tree, rather than like a hub and spoke network.

Another way to understand the structure of inside trading networks is to compare the concentration of tips given by a tipper across all of his tippees to the concentration of tips received by a tippee from all of his tippers. In particular, I calculate the fraction of a tipper's total tips that are given to each tippee. Using these fractions I compute a Hefindahl index of concentration. For the average tipper, the Herfindahl index of tips is 85%. In contrast, for the average tippee, the Herfindahl index is 95%. The difference in concentration ratios implies that tippers spread information among multiple tippees, but tippees only receive information from few tippers. This is consistent with the network statistics above, in which connections flow outward from a central node like branches on a tree.

Next, as networks increase in size, they have a smaller fraction of female tippers, the ages of tippers and tippees decrease, and there exist fewer family connections and more business connections. Friendship connections remain roughly the same across network size. The median geographic distance also increases as networks get larger. As networks increase in size, the average and median amount invested per tippee increase. The median profit increases as well, though percentage returns decrease. Finally, the time lapse between tips is lowest in the larger networks. These results suggest that large networks include professional traders who trade larger stakes and have lower percentage returns. Since the larger networks still experience time delays between tips, it is likely that the returns are lower because they are receiving the tip after insider trading has already begun to move stock prices.

The sparseness of insider trading networks is more similar to criminal networks than innocuous social networks. For example, the Global Salafi jihad (GSJ) terrorist network has a diameter of nine among 356 members and the Methworld narcotics trafficking network has a diameter of 17 among 924 members (Chen, 2006). In contrast, noncriminal social networks of person-to-person communication have shorter diameters, consistent with small-world networks. For example, a network of university friendships has a diameter of four among 217 members, a network of local physicians who share information about a new medical innovation has a diameter of five among 241 members, and a network of high school friendships has a diameter of six among 70 students.[7] As a comparison, the sizes of the SAC network (64 members) and the Rajaratnam network (50 members) are slightly less than the high school friends network (70 members), but they have diameters that are much longer: 13 in the SAC network and ten in the Rajaratnam network. This means that the large insider trading networks are more dispersed than the high school friendship network.

8. Insider trading and financial outcomes

In this section, I test whether the social relationships that underlie insider trading networks affect financial outcomes. First, I investigate whether insider trading affects stock prices. Second, I test whether the price impact of a trade depends upon the identities and relationships of inside traders. Third, I test whether social networks influence individual gains from insider trading.

8.1. Insider trading and stock prices

Though many papers infer the presence of insider trading before corporate announcements based on price and volume run-ups (Jarrell and Poulsen, 1989; Schwert, 1996; Chae, 2005; Christophe, Ferri and Hsieh, 2010), there is almost no evidence based on direct observations of insider trading. The exceptions are Meulbroek (1992) which

[7] See the network statistics for Highschool, Residence, and Physicians at http://konect.uni-koblenz.de/networks.

studies 183 insider trading events from the 1980s, Cornell and Sirri (1992) which studies one event from 1982, and Chakravarty and McConnell (1999) which studies one case from 1984. The results from these studies provide mixed evidence on the price impact of insider trading. Therefore, it is important to first test whether insider trading affects stock returns using my data.

In particular, I estimate the following model using a panel of daily observations from 120 trading days before the announcement to one trading day before the announcement:

$$r_{it} = \alpha + \beta \,\text{Insider trading}_{it} + \delta \ln(1 + \text{Volume}_{it}) + \gamma \text{Factors}_{it} + \kappa_i + \lambda_t + \varepsilon_{it}, \quad (1)$$

where i indexes the event (e.g., Abaxis Q3 2007 Earnings) and t indexes days in event time $(-120, \ldots, -1)$. The dependent variable, r_{it}, is the stock return of event firm i on day t and *Insider trading*$_{it}$ is a measure of the extent of insider trading in event firm i on day t. *Volume*$_{it}$ is the daily volume for event firm i, *Factors*$_{it}$ are the daily Fama-French factors (market, *SMB*, and *HML*) in event time. I also control for event fixed effects (κ_i) and event-time fixed effects (λ_{it}) in some specifications. The event fixed effects account for all time-invariant explanatory variables in the period from -120 to -1, including firm characteristics and event characteristics. The event-time fixed effects are dummy variables for each event day, from -120 to -1, which account for any common factors that affect returns for each day in the period before an announcement. Thus, this model is designed to control for all unobserved time-invariant factors related to an event, all unobserved factors related to a particular day in the period before the event is announced, and the most important time-varying factors, including volume and market-wide risk factors, in order to isolate whether insider trading on a particular day has any effect on stock returns. The data include 410 events in which stock prices are available and in which inside traders traded common shares. Stock returns and market factors are multiplied by negative one for negative events.

Table 10 presents the results of the regressions. In column 1, *Insider trading*$_{it}$ is measured with a dummy variable for the presence of any insider trading on day t. The estimated coefficient is positive and statistically significant. Stock returns are 20 basis points higher on days in which insiders trade.[8] In column 2, the number of unique insider traders that trade on a particular day is also positively and significantly related to stock returns. This result holds after controlling for event-time fixed effects in column 3. Columns 4–6 shows that when inside traders buy more shares, returns are higher. This result holds after controlling for event-time fixed effects and when only including days in which inside traders are active.

These results provide consistent evidence that illegal insider trading has a significant effect on stock prices. This implies that insider trading moves stock prices closer to their fundamental values, and hence, makes prices more efficient. Though prior research on information diffusion through social networks shows that information sharing can lead to greater personal gains (Cohen, Frazzini and Malloy, 2008) or correlated stock market behavior of individual traders (Hong, Kubik and Stein, 2005), my results show that information diffusion through social interaction helps move prices toward their full-information values.

8.2. Inside traders' characteristics and stock returns

Though the above results show that insider trading makes prices more efficient, it is not clear whether the underlying social networks influence this relationship. For instance, is the price impact greater if the tipper is the trader's brother, rather than a business associate? Moreover, does the identity of the inside trader affect a trade's price impact?

On one hand, the identity of the trader or the relationship between the tipper and the trader could influence the aggressiveness of an inside trader. Perhaps an inside trader has greater confidence in information he receives from his brother, and hence, trades large volumes. On the other hand, the social relationships and identities of inside traders may be unrelated to price impact. In the setting of illegal insider trading, the quality of information may be sufficiently uniform that all insiders trade aggressively. Therefore, whether a trader receives information from his brother or a business associate, the credibility of the information is roughly the same.

To test these hypotheses, I estimate the same model as above, except I replace the daily volume of inside trading by variables that measure the characteristics of the traders for each day in event time. In particular, I include the average age of inside traders per day, the fraction of insiders that are female, the wealth of inside traders, and the fraction that are buy-side managers and analysts. I also include measures of centrality: instrength (the number of tips received by an average inside trader), outstrength (the number of tips given by an average insider trader), network size (the size of the average trader's network), and position in the tip chain.[9] I also include variables that measure the geographic distance between tippers and traders and the fraction of relationships between tippers and traders that are business associates, family members, and friends. As before, these tests are conducted using event-firm fixed effects and market factors. Thus, these tests identify for a particular event, whether time-series changes in the characteristics of inside traders influence changes in stock returns.

I find that inside traders' age, gender, wealth, occupation, and network positions do not have significant relationships with stock returns. However, when traders receive information from a family member, stock returns are significantly higher. This result holds after controlling for event fixed effects and event-time fixed effects. This could

[8] This is smaller than the estimates in Meulbroek (1992) and Cornell and Sirri (1992), though I control for event fixed effects, volume, and market risk factors, and these prior papers do not.

[9] I use instrength and outstrength rather than a recursive measure of centrality, such as eigenvector centrality, because strength measures are not influenced by network size, whereas eigenvector centrality is. Since there is large variation in network size, eigenvector centrality is less comparable across individuals in different networks.

Table 10
Insider trading and daily returns.

This table presents fixed effects regresssions on daily stock returns for the event firms in the sample. Observations are from 120 trading days before the public announcement of the event to one day before the announcement. All regressions include event fixed effects, which controls for all characteristics of the event and of the firm that are time invariant over the 120 trading days before the announcement. All regressions also include ln(1+daily volume) and daily returns for the market, *SMB*, and *HML* factors. Event-time fixed effects are dummy variables for days in the $(-120, -1)$ period. Insider trading days only include observations in which an insider traded on a particular day. Insider trading dummy is a dummy variable that takes the value of one if an insider traded on a particular day. ln(1+# of inside traders) is the log of one plus the number of unique inside traders that trade on a particular day. ln(1+# of shares traded by inside traders) is the log of one plus the total number of shares traded by insiders on a particular day. Table 1 describes the sample. *p*-values from standard errors clustered at the event level are presented in parentheses. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

	Dependent variable: daily stock return (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Insider trading dummy	0.204***					
	(0.006)					
ln(1+# of inside traders)		0.270***	0.197**			
		(0.001)	(0.024)			
ln(1+# of shares traded by inside traders)				0.109***	0.087***	0.288**
				(<0.001)	(0.007)	(0.049)
Control variables:						
Volume, *MKTRET*, *SMB*, and *HML*	Yes	Yes	Yes	Yes	Yes	Yes
Event fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Event-time fixed effects	No	No	Yes	No	Yes	Yes
Insider trading days only	No	No	No	No	No	Yes
Observations	48,445	48,445	48,445	48,445	48,445	2,338
Adjusted R^2	0.154	0.155	0.155	0.155	0.155	0.135

indicate that tips from family members are more reliable, which leads to more aggressive trading. In contrast, tips from business associates and friends are unrelated to stock returns. Geographic distance is also unrelated to stock returns. These results are presented in Internet Appendix Tables 7 and 8.

Overall, most of the characteristics of inside traders are unrelated to stock returns. As I mentioned, this could be because the information on which these trades are made is highly credible, regardless of its provenance, though there is some evidence that stock returns are higher if inside traders receive information from a family member, which is consistent with more aggressive trading when information is more credible. It is important to note that these results do not mean that social networks are unimportant for stock prices. Rather they imply that I cannot identify any variation in the type of social network that is related to variation in the price impact of the information.

8.3. Inside trading networks and individual gains

Next, I test whether underlying social networks influence individual gains from insider trading. Theories of information networks predict that individuals that are more central use their information advantage to capture greater profits (Ozsoylev and Walden, 2011; Walden, 2013). These predictions can be loosely applied to the setting of insider trading, though there are some key assumptions that are violated. Most importantly, these theories assume there is no cost to sharing information: investors are price-takers and there are no legal consequences to sharing information.

Table 11 presents the results of cross-sectional regressions of inside traders' gains on their network centrality. The sample only includes people that traded on inside information, not people who just passed information without trading. The dependent variable in columns 1–3 is ln(returns), where returns are in percentages. I winsorize returns at the 1% and 99% levels to minimize the impact of outliers. I use logged returns because the raw returns are highly skewed in the cross-section. The dependent variable in columns 4–6 is logged gains and losses avoided.

To measure an inside trader's network centrality, I use outstrength, instrength, outdegree, and indegree, where outdegree (indegree) measures the number of different tippees (tippers) a trader has. I also include network size and average position in a tip chain as explanatory variables. For example, Roomy Khan from Fig. 1, has an outstrength of 19, an instrength of 6, an outdegree of 7, and an indegree of 4. Her network size is 50, for the 50 insider traders in the Raj Rajaratnam network, and her average position in a tip chain is 1.3. I also control for the amount of money an inside trader invests and a dummy for whether the trader used options in any trade. Standard errors are robust to heteroskedasticity.

The results in Table 11 show that inside traders who receive more tips (instrength) from more people (indegree) realize higher returns and profit. When instrength and indegree are both included in the same specification, only instrength has a significant relation with insider trading gains. Second, inside traders in larger networks have higher returns and greater profits. Third, greater distance in a tip chain is associated with smaller profits, but is unrelated to returns. Finally, returns are significantly less when an inside trader invests more money and significantly greater when he uses options. In unreported tests, I interact network size with the strength and degree measures. There is no consequential change to the results. In other tests, I also control for age, gender, and the relationship between the trader and tipper and find no significant relationships.

Table 11
Insider characteristics and individual trading gains.
This table presents OLS regresssions on daily stock returns for the event firms in the sample. Observations are for all inside traders that traded securities for whom data are available. The dependent variable in columns 1–3 is the log of one plus the inside trader's total return over all trades, calculated as total profit divided by total invested. The dependent variable in columns 4–6 is the log of the inside trader's total profit over all trades. Network instrength is the number of tips received by a trader in the entire sample. Network outstrength is the number of tips given by a trader in the entire sample. Network indegree is the number of different tippers that gave tips to an insider. Network outdegree is the number of tippees to whom a trader gave tips. Network size is the number of inside traders in a trader's network of insiders. ln(Amount invested) is the total dollar amount of the inside trader's investments. Tip chain distance is the number of links from the original source. Uses options is a dummy variable that indicates if a trader ever traded options on inside information. Table 1 describes the sample. p-values from robust standard errors are presented in parentheses. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

	ln(Return)			ln(Profit)		
	(1)	(2)	(3)	(4)	(5)	(6)
Network outstrength	−0.025		0.010	−0.030		−0.022
	(0.225)		(0.702)	(0.489)		(0.753)
Network instrength	0.085***		0.085***	0.217***		0.215***
	(<0.001)		(<0.001)	(<0.001)		(<0.001)
Network outdegree		−0.086	−0.130		−0.009	−0.029
		(0.153)	(0.129)		(0.918)	(0.848)
Network indegree		0.126*	−0.023		0.365**	0.005
		(0.078)	(0.789)		(0.022)	(0.976)
Network size	0.012**	0.012**	0.014**	0.042***	0.041***	0.042***
	(0.029)	(0.042)	(0.023)	(<0.001)	(<0.001)	(<0.001)
Tip chain distance	−0.007	0.015	−0.011	−0.231***	−0.191**	−0.232***
	(0.906)	(0.809)	(0.856)	(0.009)	(0.036)	(0.010)
ln(Amount invested)	−0.309***	−0.276***	−0.311***			
	(<0.001)	(<0.001)	(<0.001)			
Use options	1.545***	1.665***	1.545***	1.237***	1.239***	1.237***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Constant	7.080***	6.698***	7.147***	10.988***	10.988***	10.993***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Observations	249	249	249	399	399	399
Adjusted R^2	0.311	0.281	0.311	0.247	0.189	0.243

In sum, since greater instrength is positively related to investment returns, not just dollar profits, these results suggest that more central inside traders get more valuable information, not just more information. Second, because indegree has less explanatory power than instrength, these results imply that having many tippers is less valuable than having many tips, even if they come from relatively few tippers. Finally, controlling for a trader's number of tippers and the number of tips they give, all else equal, insiders in large networks receive more valuable information.

9. Generalizability

The results presented so far paint a detailed picture of illegal insider trading networks. However, my results are not based on a random sample. Instead, some types of inside traders are likely over-sampled relative to the population, and other types are likely under-sampled. Unfortunately, it is impossible to know which types are which because I would need to observe both inside traders that are caught and inside traders that are not caught. Compared to studies of corporate fraud, understanding selection bias in illegal insider trading is particularly challenging because I cannot even observe a benchmark sample of individual traders who were not charged with a crime, as can be observed in a sample of firms not charged with corporate fraud.[10]

Though generalizability is a problem common to virtually all studies of illegal activity, it would be useful to have some sense of how my sample differs from the population at large. One approach to evaluate the generalizability of the findings is to consider how regulators detect and prosecute inside trading. Biases in the detection methods or incentives of regulators might help to understand how my sample differs from the general population. A detailed description of the ways in which inside traders are caught is presented in the Internet Appendix. I summarize the main points here.

Regulatory authorities are more likely to investigate potential insider trading if a trader makes larger trades, realizes greater amount of profits or losses avoided, and if the conduct is ongoing or widespread (U.S. Securities and Exchange Commission, 2013; Financial Industry Regulatory Authority, 2015). In addition, inside traders in larger networks are more likely to get caught because more traders will create greater abnormal trading activity and because there are more people in the network who may reveal themselves to the regulators, intentionally or accidentally. In addition, the SEC's lawyers are evaluated based, in part, on the amount of penalties that they collect from their cases. Because penalties are typically based on the size of an inside trader's ill-gotten profits and losses avoided, SEC lawyers have an incentive to find inside traders that make large gains.

This discussion suggests that biases in detection and the likelihood of prosecution will lead my sample to over-represent serial inside traders who make many large trades, compared to the average inside trader in the

[10] Such a benchmark would still be insufficient because there are firms that commit fraud that are not detected (Wang, Winton and Yu, 2010).

population. In contrast, my sample is likely to under-represent one-time opportunistic traders who make small investments.

It is tempting to compare other characteristics of large inside traders compared to small inside traders to infer selection bias. For instance, in my sample, inside traders in larger networks are younger and are more likely to receive information from business associates than inside traders in smaller networks. However, it is not certain that this comparison applies to the general population. Perhaps the inside traders in large networks that are caught are different than the inside traders in large networks that are not caught. Therefore, to be conservative, I acknowledge that it is impossible to know all of the dimensions in which my sample varies from the general population.

9.1. Inside traders compared to their neighbors

Another way to assess the generalizability of the results is to compare inside traders to their neighbors. For the 448 inside traders that I can identify in the LNPRD, I pick a neighbor of the same gender that lives on the same street as the inside trader with the closest street number to the inside trader's street number. I require the neighbor to have a social security number and date of birth recorded in the LNPRD. Choosing a comparison sample from the same neighborhood and of the same gender helps to control for wealth, age, and occupation, and highlights the remaining differences between inside traders and non-insiders.[11]

I find that inside traders are statistically different than their neighbors in many ways. Inside traders are younger, less likely to own real estate, and have fewer family members and significantly more associates. This could reflect that inside traders have large external networks with whom they are more likely to share information. In addition, inside traders are considerably more likely to have a criminal record (53.7%) than their neighbors (12.8%). Of the 246 instances of criminal records, the overwhelming majority of identifiable criminal charges are for traffic violations. Though the greater prevalence of criminal records among inside traders could reflect that they are just more likely to get caught breaking the law than are their neighbors (whether speeding or illegal trading), it seems more likely that inside traders are either less risk averse or generally have less respect for the rule of law than their neighbors. See Internet Appendix Table 9 for more details.

9.2. Selection on guilt

A final selection issue is whether the facts presented in the documents are true. First, the track record of the DOJ is impressive: between 2009 and 2014, the DOJ has won 85 cases and lost just once. The DOJ's track record could be impressive because it only brings cases it can win. Even so, this suggests that the facts reported in the cases that I use are likely to be true. Second, in SEC cases that are subsequently dropped, the facts presented in the case are typically not contested. The cases are usually dropped based on technical issues about what constitutes insider trading. For example, as discussed above, some defendants argue that they did not violate insider trading rules because they were three to four links removed from the original source, but do not dispute the facts of the case.

10. Conclusion

This paper provides new evidence on the importance of social networks for the diffusion of private information among investors by studying illegal insider trading networks. The paper provides new insights into the profile of inside traders, the social ties that connect them, and the information they share. I find that inside traders are connected by strong social ties based on meaningful social relations and shared demographic backgrounds.

The results show that information about significant corporate events tends to originate from corporate insiders, often top executives. Information proceeds from the original source through a number of links before ending up with buy-side analysts and managers. Along the way, information tends to flow from younger people to older people, from children to parents, and from subordinates to bosses in close geographic proximity. Tippers and tippees are more commonly friends and family in the early links of an information chain and more commonly business associates in later links. Networks of inside traders are sprawling, rather than centralized, where larger networks are more likely based on business relationships than family or friends.

Second, the results show that insider trading is associated with efficient stock price movements. When there is more insider trading, stock prices move closer to their fundamental values. Inside traders realize significant gains from their investments of about 35% over 21 days. Inside traders who receive more tips and are in larger networks realize significantly larger gains.

The results of this paper inform the current debate about the legality of insider trading. The 2014 decision in U.S. v. Newman, significantly narrowed the definition of illegal insider trading. Under this new ruling, inside traders that are multiple links removed from the original source are less likely to be prosecuted. My data reveal that these people are overwhelmingly professional portfolio managers who make many insider trades with large sums of money. In January 2016, the US Supreme Court agreed to review this precedent. The results in this paper may help the Court to understand the consequences of its decision.

Finally, from an academic point of view, the results of this paper validate existing findings and suggest new directions for future research. In particular, the paper shows that social connections based on trusting relationships are an important mechanism in the diffusion of important information across market participants, as suggested by Hong and Stein (1999). More broadly, this paper contributes to a burgeoning field of finance concerned with

[11] Because many fields of LNPRD data are provided at the state level, missing data (i.e., licensing, criminal records) will be missing at the state level, too. Therefore, using neighbors mitigates any concerns about selectively missing observations. I only collect one random neighbor as a counterfactual observation because identifying neighbors in the data requires substantial search time and effort.

the role of social interactions in financial decision-making, which Hirshleifer (2015) calls “social finance”.

References

Andrei, D., Cujean, J., 2015. Information percolation, momentum, and reversal. University of California, Los Angeles and University of Maryland. Unpublished working paper.

Augustin, P., Brenner, M., Subrahmanyam, M.G., 2014. Informed options trading prior to M&A announcements: insider trading?. McGill University and New York University. Unpublished working paper.

Barber, B., Odean, T., 2001. Boys will be boys: gender, overconfidence, and common stock investment. Quarterly Journal of Economics 116, 261–292.

Bhattacharya, U., 2014. Insider trading controversies: a literature review. Annual Review of Financial Economics 6, 385–403.

Bhattacharya, U., Daouk, H., 2002. The world price of insider trading. Journal of Finance 57, 75–108.

Brown, J.R., Ivković, Z., Smith, P.A., Weisbenner, S., 2008. Neighbors matter: causal community effects and stock market participation. Journal of Finance 63, 1509–1531.

Calvet, L.E., Campbell, J.Y., Sodini, P., 2009. Fight or flight? Portfolio rebalancing by individual investors. Quarterly Journal of Economics 124, 301–348.

Chae, J., 2005. Trading volume, information asymmetry, and timing information. Journal of Finance 60, 413–442.

Chakravarty, S., McConnell, J.H., 1999. Does insider trading really move stock prices? Journal of Financial and Quantitative Analysis 34, 191–209.

Chen, H., 2006. Intelligence and Security Informatics for International Security: Information Sharing and Data Mining. Springer Science+Business Media, Inc., New York, NY.

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

Cohen, L., Frazzini, A., Malloy, C., 2008. The small world of investing: board connections and mutual fund returns. Journal of Political Economy 116, 951–979.

Cohen, L., Frazzini, A., Malloy, C., 2010. Sell side school ties. Journal of Finance 65, 1409–1437.

Cornell, B., Sirri, E.R., 1992. The reaction of investors and stock prices to insider trading. Journal of Finance 47, 1031–1059.

Del Guercio, D., Odders-White, E.R., Ready, M.J., 2013. The deterrence effect of SEC enforcement intensity on illegal insider trading. University of Oregon and University of Wisconsin–Madison. Unpublished working paper.

Dhar, R., Zhu, N., 2006. Up close and personal: investor sophistication and the disposition effect. Management Science 52, 726–740.

Financial Industry Regulatory Authority, 2015. Monitoring for insider trading and understanding FINRA’s regulatory tip process. Online Webinar: https://www.finra.org/industry/monitoring-insider-trading-and-understanding-finra%E2%80%99s-regulatory-tip-process.html.

Fishe, R.P., Robe, M.A., 2004. The impact of illegal insider trading in dealer and specialist markets: evidence from a natural experiment. Journal of Financial Economics 71, 461–488.

Goldenberg, J., Levy, M., 2009. Distance is not dead: social interaction and geographical distance in the Internet era. Computers and Society 2, 1–22.

Guiso, L., Sapienza, P., Zingales, L., 2009. Cultural biases in economic exchange? Quarterly Journal of Economics 124 (3), 1095–1131.

Han, B., Yang, L., 2013. Social networks, information acquisition, and asset prices. Management Science 59, 1444–1457.

Hirshleifer, D.A., 2015. Behavioral finance. Annual Review of Financial Economics 7, 133–159.

Hong, H., Kubik, J.D., Stein, J.C., 2005. Thy neighbor’s portfolio: word-of–mouth effects in the holdings and trades of money managers. Journal of Finance 60, 2801–2824.

Hong, H., Stein, J.C., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. Journal of Finance 54, 2143–2184.

Hvide, H.K., Östberg, P., 2015. Stock investments at work. Journal of Financial Economics 117, 628–652.

Jarrell, G.A., Poulsen, A.B., 1989. Stock trading before the announcement of tender offers: insider trading or market anticipation? Journal of Law, Economics and Organization 5, 225–248.

Korniotis, G.M., Kumar, A., 2011. Do older investors make better investment decisions? Review of Economics and Statistics 93, 244–265.

Massa, M., Simonov, A., 2006. Hedging, familiarity and portfolio choice. Review of Financial Studies 19, 633–685.

Mateos, P., 2007. A review of name-based ethnicity classification methods and their potential in population studies. Population, Space and Place 13, 243–263.

McPherson, M., Smith-Lovin, L., Cook, J.M., 2001. Birds of a feather: homophily in social networks. Annual Review of Sociology 27, 415–444.

Meulbroek, L.K., 1992. An empirical analysis of illegal insider trading. Journal of Finance 47, 1661–1699.

Morselli, C., 2009. Inside Criminal Networks. Studies of Organized Crime, Vol. 8. Springer, New York, NY.

Ozsoylev, H.N., Walden, J., 2011. Asset pricing in large information networks. Journal of Economic Theory 146, 2252–2280.

Ozsoylev, H.N., Walden, J., Yavuz, M.D., Bildak, R., 2014. Investor networks in the stock market. Review of Financial Studies 27, 1323–1366.

Schwert, G.W., 1996. Markup pricing in mergers and acquisitions. Journal of Financial Economics 41, 153–192.

Shiller, R.J., Pound, J., 1989. Survey evidence on diffusion of interest and information among investors. Journal of Economic Behavior and Organization 12, 47–66.

Smith, J.A., McPherson, M., Smith-Lovin, L., 2014. Social distance in the United States: sex, race, religion, age, and education homophily among confidants, 1985 to 2004. American Sociological Review 79, 432–456.

Stein, J.C., 2008. Conversations among competitors. American Economic Review 98, 2150–2162.

U.S. Securities and Exchange Commission, 2013. Enforcement Manual. Securities and Exchange Commission Division of Enforcement. Washington, D.C.

Walden, J., 2013. Trading, profits, and volatility in a dynamic information network model. University of California, Berkeley. Unpublished working paper.

Wang, T.Y., Winton, A., Yu, X., 2010. Corporate fraud and business conditions: evidence from IPOs. Journal of Finance 65, 2255–2292.