INFORMATION NETWORKS: EVIDENCE FROM ILLEGAL INSIDER TRADING TIPS

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ABSTRACT

This paper exploits detailed data from illegal insider trading cases to study how private information diffuses across investors through social networks. I find that the majority of inside traders are connected through family and friendship links and a minority are connected through professional relationships. Traders cluster by age, occupation, gender, and location. Using inside information, traders earn prodigious returns of about 35% over 21 days. Traders farther from the original source earn lower percentage returns, but higher dollar gains. More broadly, this paper provides some of the first evidence on the transmission of information between stock market participants using direct observations of person-to-person communication.

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This paper exploits detailed data from illegal insider trading cases to study how private information diffuses across investors through social networks. I find that the majority of inside traders are connected through family and friendship links and a minority are connected through professional relationships. Traders cluster by age, occupation, gender, and location. Using inside information, traders earn prodigious returns of about 35% over 21 days. Traders farther from the original source earn lower percentage returns, but higher dollar gains. More broadly, this paper provides some of the first evidence on the transmission of information between stock market participants using direct observations of person-to-person communication.

Though information is central to understanding financial markets, we know relatively little about how private information spreads among market participants. A prominent line of research starting with Hayek (1945) argues that private information is revealed through trading and that market prices convey all relevant information.[1] An alternative line of research argues that private information could also be conveyed through non-market social interactions between investors (Hong and Stein, 1999). A serious concern with this claim is that the supporting empirical evidence relies on imperfect proxies for social interaction, such as geographic proximity (Hong, Kubik, and Stein, 2005; Brown, Ivković, Smith, and Weisbenner, 2008), common educational backgrounds (Cohen, Frazzini, and Malloy, 2010), and correlated trades (Ozsoylev, Walden, Yavuz, and Bildak, 2014). While these proxies may capture social interactions, they could also reflect homophily among people of similar backgrounds. There is currently almost no direct evidence of actual communication between individual investors.

In this paper, I use data from illegal insider trading cases to present some of the first direct evidence on the diffusion of private information across market participants. I provide an in-depth picture of where information originates, to whom and how fast it spreads, how tippers and tippees know each other, and the trading behavior and investment returns of individual investors. Combining all of the features of the data, I construct information networks of inside traders connected through word-of-mouth communication.

Figure 1 presents an illustrative example of an information network in the data. This network is centered on Raj Rajaratnam, the former hedge fund manager of the Galleon Group. The connections between people in the network represent direct observations of word-of-mouth exchange of private information. For example, on March 14, 2007, an unidentified credit analyst at UBS learned through his job that Hellman & Friedman would acquire Kronos. He tipped his friend and roommate, Deep Shah, an analyst at Moody's, who tipped a friend of the family, Roomy Khan. The following day, Roomy Khan tipped a family friend, Shammara Hussain, two former business associates, Jeffrey Yokuty and his boss, Robert Feinblatt, and another friend, Thomas Hardin. On March 19th, Hardin tipped his friend, Gautham Shankar, who tipped Zvi Goffer, David Plate, and unidentified traders at the investment firm Schottenfeld Group. David Plate subsequently tipped

[1]Seminal papers in this vein include Fama (1970), Grossman and Stiglitz (1980), and Kyle (1985).

others at Schottenfeld and Goffer tipped his long-time friend, Joseph Mancuso. The acquisition was officially announced at 9 am on March 23, 2007. As a whole the group of inside traders realized gains of $2.9 million on this tip.

Illegal insider trading cases provide a number of important advantages for studying information networks. Prosecutors of insider trading cases must provide detailed records to prove that material, nonpublic information was shared between traders. This means that the information must be factual, rather than speculative. Second, for the trading to be illegal, the information must be private. This rules out public sources of information that would confound the study of private information exchange. Third, prosecutors must provide credible evidence of the timing and content of actual information exchange and trading activity. Finally, prosecutors must establish the type of social relationship between inside traders that would facilitate sharing private information.

To exploit the richness of insider trading cases, I hand collect data from the narratives recorded in all of the cases filed by the Securities and Exchange Commission (SEC) and the Department of Justice (DOJ) between 2009 and 2013. The data cover 465 corporate events, 351 firms, and 611 inside traders. Using the original source data from the SEC and DOJ, I record the date that information is shared, the amount invested, the timing of trades, and the types of securities traded. I also record the type of social relationship between inside traders, such as family, friends, and business associates. Combining the SEC and DOJ data with data from professional networking websites and the LexisNexis Public Records database, I fill in missing data on age, location, education, and occupation of the inside traders in the sample. In sum, these data provide an unprecedented view of how investors share private information.

Using this comprehensive data, this paper's main objective is to present a series of stylized facts about the flow of information across inside traders. First, I present a detailed profile of individual traders, the events on which they trade, the firms that are the subject of the information, and the traders' investment returns. Second, I present a range of findings about how insiders are connected to each other through social relationships. Third, I analyze the flow of information from the original source to the final tippee. Finally, I present the characteristics of information networks as a whole.

First, the data show that insider tips are about specific corporate events that have meaningful effects on stock prices. Merger-related events account for 51% of the sample, followed by earnings-related events, accounting for 26%. The remaining events include clinical trial and regulatory announcements, sale of new securities, and operational news such as CEO turnovers.

Trading in advance of these events yields large returns. Across all types of events, the average stock return from the date of the original leak of information to the official announcement of the event is 34.9% over an average holding period of 21 trading days. Clinical trials generate the largest average gains at 101% in 9 trading days. M&As generate average returns of 43% in 31 trading days. Earnings generate relatively smaller returns of 14% in 11 days.

The firms that are the subject of insider trading tend to be large. The median sample firm's market equity is $1 billion, comparable to the NYSE's median equity of $1.2 billion in 2011. Compared to the universe of listed firms and firms targeted in acquisitions, high tech pharmaceutical and electronics firms are overweighted and utilities and financial intermediaries are underweighted.

Insider trading involves a wide array of people. The average age of inside traders is 43 years and about 10% are women. Compared to the general population, they tend to reside in New York, Florida, and California, and tend not to reside in Texas, Ohio, and Virginia. 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, traders earn about $72,000 per tip at the median. The most common occupation among insiders is top executive, including CEOs, CFOs, and directors. There are a significant number of buy side investment managers and analysts, as well as sell side professions, such as lawyers, accountants, and consultants. The sample also includes a number of non-"Wall Street" types, such as small business owners, real estate professionals, doctors, engineers, nurses, teachers, and physical therapists.

The next set of results document the social connections between inside traders. Of the 445 pairs of tippers and tippees in the sample, 23% are family members, 38% are business associates, and 38% are friends, including pairs that are both family members and business associates. Sibling and parental relations are the most common type of family connections. Of business associates, about half of the relationships are between a boss and subordinate or client and agent. The remaining half are associates of equal status. Across the whole sample, I find that 74% of pairs of insiders met each other before college, 19% met during college, and 7% met after completing their education. Excluding family members, about 43% of pairs met during college. These results suggest that common educational background is a valid proxy for current information flows (Cohen, Frazzini, and Malloy, 2010), though family ties are a stronger proxy.

People who share inside information tend to live close to each other. The median distance between a tipper and his tippee is 26 miles. This result validates the use of local neighborhoods as a proxy for social interaction as used in many papers on peer effects in finance (e.g., Brown, Ivković, Smith, and Weisbenner, 2008). However, a significant fraction of pairs do not live close to one another. The 75th percentile of distance is 739 miles. Geographic connections between locations are not random. For instance, people in New York are likely to be connected to people in Miami and San Francisco; people in Southern California are likely to be connected to people in Northern California. In contrast, people in Chicago, Dallas, and Atlanta have fewer connections than expected based on the general population.

I next investigate the direction of information flows. Though tippers tend to tip other people in their same profession, top executives are three times more likely to be a tipper than a tippee. In contrast, buy side managers and analysts are tippers about half as often as they are tippees. Information tends to flow from subordinates to bosses and from younger tippers to older tippees. Women are more likely to tip and be tipped by other women. The original source of a tip depends upon the type of event that the information is about. Inside information about mergers is leaked by both acquirer and target employees, and external firms, such as law firms and investor relations firms. Earnings information is likely to be leaked by an accounting firm employee. In addition, a significant fraction of leaks are originated by people who secretly misappropriated the information from a friend or family member.

To investigate how information flows across a network of traders, I identify "tip chains" in the networks. A tip chain is the ordered set of traders through which a particular tip passes. I find that as information diffuses away from the source, top executives and mid-level managers are less likely to send or receive tips. Instead, after three degrees of separation from the original source, buy side managers and analysts account for the majority of information sharing. The first links in a tip chain are more likely to be friends and family, but as the information diffuses further from the source, business links become more prevalent. People who are closer to the original source of the information earn higher returns, but invest smaller amounts. People further from the source invest larger amounts and make smaller percentage returns, but larger dollar gains. The speed of information also increases as it moves further from the source.

Finally, the last set of results document the structure of the networks of inside traders. Of 184 insider networks in the sample, 59 contain only one person. These are people who learn inside information, but do not tip anyone else. On the other end of the spectrum, the largest network has 50 members, and the second largest has 46. In the cross-section of networks, larger networks become less dense with fewer clusters of links. This implies that peripheral members are not closely connected to central members of a network. Instead, information networks sprawl outward. Larger networks have younger members and fewer women who are more likely connected through business relationships, compared to smaller networks.

Using illegal insider trading cases to study information networks is not without limitations. The most important limitation is that insider trading cases do not represent a random sample of all information flows. Because insider trading is illegal, it is potentially costly to share information. To overcome the legal costs of insider trading, investors might only share tips about events with very large payoffs. They might also prefer to share information with trusted confidants, which would not be necessary if insider trading was legal. The second key limitation is that the sample of inside traders is based on those who were caught. This could bias the sample towards the most egregious violations, or alternatively, the least sophisticated inside traders. I discuss these limitations in greater detail later in the paper and conclude that the advantages of the data far outweigh their limitations.

This paper contributes to two areas of research. First, to my knowledge, this paper presents the most detailed description of illegal insider trading to date. The most similar paper is Meulbroek (1992), which uses SEC cases from the 1980s to show that insider trades affect takeover prices. Subsequently, a number of other papers test whether illegal insider trading influences stock prices and takeover premia (Meulbroek and Hart, 1997; Chakravarty and McConnell, 1999; Fishe and Robe, 2004). Another set of papers considers whether the intensity of enforcement of insider trading laws affects financial markets (Bhattacharya and Daouk, 2002; Bushman, Piotroski, and

Smith, 2005; Bhattacharya and Marshall, 2012; Del Guercio, Odders-White, and Ready, 2013). In contrast, this paper focuses on the flow of information through the social connections of traders.

Second, this paper contributes to a broader research agenda on social interactions in finance. Most directly, this paper contributes to the new field of information networks. Theoretical models predict that the structure of information networks affect price informativeness, liquidity, and trading strategies (Colla and Mele, 2010; Ozsoylev and Walden, 2011; Walden, 2013; Han and Hirshleifer, 2013; Han and Yang, 2013). However, apart from Ozsoylev, Walden, Yavuz, and Bildak (2014), which uses correlated trades to infer social connections, there is little empirical evidence on information networks. This paper also relates to research on peer effects in economics and finance. Manski (2000) argues that information sharing is one of the primary forms of non-market social interaction among economic agents. Recent research shows that peers influence stock market activity (Hong, Kubik, and Stein, 2004; Ivković and Weisbenner, 2007; Pool, Stoffman, and Yonker, 2014), CEO compensation and investment (Shue, 2013), and entrepreneurship (Lerner and Malmendier, 2013). Rather than relying on instrumental variables, this paper uses direct observation of social interactions to understand how information travels through a set of peers.

I. Legal Environment and Sample Selection

According to the Securities and Exchange Commission (SEC), insider trading refers to "buying or selling a security, in breach of a fiduciary duty or other relationship of trust and confidence, while in possession of material, nonpublic information about the security."[2] Under U.S. law, insider trading is both a crime punishable by monetary penalties and imprisonment and a civil offense requiring disgorgement of illegal profits and payment of civil penalties. Criminal offenses are charged by the Department of Justice (DOJ) and civil offenses are charged by the SEC. Civil and criminal charges can be made at the same time for the same offense. Criminal charges are much less common, because criminal law requires evidence of guilt beyond a reasonable doubt in order to convict someone of a crime. In contrast, civil cases only require that it shows guilt based on the preponderance of the evidence.

[2]From the SEC's website: http://www.sec.gov/answers/insider.htm.

Prosecution of illegal insider trading usually falls under Rule 10b-5 of the Securities Act of 1934. Whether a trade is covered by Rule 10b-5 is based on two theories. The classical theory applies to corporate insiders that purchase or sell securities on the basis of material, nonpublic information. Insiders include both employees of the firm and others who receive temporary access to confidential information, such as externally hired lawyers and accountants. The misappropriation theory applies to anyone who uses confidential information for gain in breach of a fiduciary, contractual, or similar obligation to the rightful owner of the information (typically the firm). For more detail on the legal environment of insider trading see King, Corrigan, and Dukin (2009).

For the study of information networks, using data from illegal insider trading cases offers certain advantages and limitations. The primary advantage is the credibility and level of detail provided in the case documentation. To support an accusation of illegal insider trading, the SEC and DOJ must provide credible evidence of how information is transmitted and how traders know each other. Thus, the documents provide explicit records of social relationships and communication, including phone records, emails, and text messages. This means I don't need to prove that an instrument for social relations is valid — the data are direct observations of social relations. The second advantage is that I can directly observe the specific information that is shared between people, rather than guessing at the nature of the information. Third, I observe specific details of trading behavior, including the timing, amount, and type of security purchased. Finally, the case data provide the identities of the insiders. This allows me to trace the information from person to person. It also allows me to match individuals to outside data sources, unlike most data on individual traders, such as that of Barber and Odean (2000).

The primary limitation of using case documents is selection bias. In particular, it is reasonable to assume that the magnitude of total insider trading is much larger than the sample of insider trading cases that are prosecuted. It is also reasonable to assume that the insiders that get caught by regulators are not randomly chosen. Instead, there are two forces that likely influence whether an insider is caught. First, sophisticated insiders are less likely to get caught than unsophisticated insiders. In the documents, I find that some insiders are oblivious to the regular monitoring of financial markets by regulators. For instance, in one case, a trader's purchases accounted for 100% of the volume of out-of-the-money call options in the days before a merger announcement, sending up red flags to regulators. The second force that influences whether an insider is caught is the extent of an insider's activity. Regulators have a greater incentive to identify insiders who are investing larger sums and making more trades.

To understand how these forces influence selection bias, consider Figure 2. This figure presents a stylized view of the population of inside traders and those that are most likely to be caught by regulators. There are four types of inside traders corresponding to the four quadrants in the figure: 1) unsophisticated with small assets under management, 2) unsophisticated with large assets, 3) sophisticated with small assets, and 4) sophisticated with large assets under management. The regulators are most likely to catch unsophisticated traders and traders making large investments.

If insiders were evenly distributed across the four quadrants, the selection of insiders that are caught would pose a serious selection bias problem. However, the population of all inside traders is not random either. Instead, it is likely to have the greatest weight on unsophisticated traders with small investments and sophisticated traders with large investments. It is unlikely that there are many unsophisticated inside traders who have large amounts of capital to invest. This means that the type 3 investors (sophisticated investors with small amounts to invest) are the type that is most likely to be underrepresented in a sample of prosecutions. Though it is impossible to know type 3's fraction of the insider population, it is plausible that sophistication and assets under management (whether in a fund or personal account) are positively related. This means that sophisticated traders likely have large amounts to invest. The empirical evidence supports these assumptions. First, the sample includes traders who trade very small amounts (a few thousand dollars). This means that the regulators do not only target the biggest insiders. Second, the sample also includes sophisticated traders who invest millions of dollars. In particular, the sample includes Steven Cohen, one of the most successful hedge fund managers of all time.

A final selection issue is whether the people accused of insider trading are found guilty. First, the track record of the DOJ is impressive: since 2009, the DOJ has won 85 cases and lost just once. Therefore, the facts reported in the cases are likely to be true. Second, the SEC cases that are subsequently dropped are not typically dropped because the facts presented in the case are incorrect. They are usually dropped based on technical issues about what constitutes insider trading. For example, in the case of Donald Longueuil, the defendant's attorneys argued that

Longueuil didn't violate insider trading rules because he didn't know the original informant, but was instead three to four links removed, and also didn't receive monetary compensation for the tip. The facts of the case were not disputed, just whether the facts constitute insider trading.

Overall, I believe the advantages of studying cases of illegal insider trading far outweigh the limitations. To my knowledge, the level of detail on information transmission in financial markets that I am able to collect from the cases is unprecedented. Nevertheless, I acknowledge that the limitations of the sample could impair the generalizability of the results.

II. Data

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. I first identify cases brought by the SEC. To identify SEC cases, I record 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. 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 information that is shared is false. 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, in which the SEC accuses "one or more unknown purchasers of securities." 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. Most DOJ cases are charged in parallel with SEC cases. In the sample, only three cases filed by the DOJ are not also charged by the SEC. In contrast, the large majority of cases filed by the SEC are not also brought by the DOJ.

I use a number of sources to collect the case documents for the insider trading cases I identify. First, I search the SEC's website for official documents. The SEC brings civil cases in two ways: civil complaints and administrative proceedings. In many cases, both a complaint and an administrative proceeding are filed. For the purposes of this paper, the legal distinction is unimportant. However, complaints 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. In contrast, administrative proceedings typically include far fewer details, providing summaries instead. Therefore, with one exception, I only include cases that have a complaint. The exception is the well publicized case against SAC Capital. The SEC does not explicitly name Steven Cohen in the complaint document, but the related administrative proceeding does.

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 DOJ cases include a number of different documents. The most useful 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. DOJ cases are usually filed against a single individual. SEC complaints are often filed against multiple people. This means in the DOJ documents, the co-conspirators remain anonymous, but they are named in the SEC documents. This makes the DOJ documents less useful. In some cases, the SEC documents discuss people anonymously too. Often cooperating witnesses are not named until the SEC brings a future case against this person. 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. I also rely on investigative journalism in media reports that uncovers the identities of people that the SEC and DOJ does not name explicitly.

This search procedure yields 334 primary source documents comprising 5,413 pages. Since the documents provide data in narrative histories, the data must be read and recorded by hand. In particular, I record five key types of information provided in the documents. First, the documents report the names, locations, employers, and ages of people named in the document. In many cases, the documents refer to people who are not officially charged by the SEC or DOJ, but who the government alleges were privy to inside information. I include these people in the data as well. Second, to provide evidence that it is reasonable that these people would share information, the filings document the social relationships between tippers and tippees. For instance, they document family relations, friendships, and co-worker relationships. Third, the documents report 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, the documents provide detailed records of the timing of information flows. These include 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, the documents provide detailed records 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 profit from the sale.

I also use the LexisNexis Public Records Database (LNPR) to help find occupation and education information for the people in my sample, particularly those who are not named as defendants, since the filings provide less information on these people. The LNPR database includes age, address, and potential employment for over 300 million people who reside in the US, whether living or dead. 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. He is also retired." I find the entry for Vlasich on LNPR using his name, city, and approximate age. The LNPR data states that his employer is Vlasich Associates. Using this information, I find his resume on an online professional networking site, which lists his college degree as an MFA from Texas Christian University in 1973 and describes his role in Vlasich Associates as the owner of a small real estate business.

Not all documents contain all information. In particular, the job titles and education of many people are not listed. To find occupations and education, 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 remove any documentation of their connection with the illegal trading charges, they may not list their old employer on online resumes. In other cases, they do not list their former employer because they were fired following the insider trading cases.

I use the LNPR to find employers that may be omitted because the LNPR lists multiple potential employers, current and past. However, the LNPR often doesn't report job title. 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. For example, the court documents state that Richard A. Hansen was the Chairman of Keystone Equities Group. A Google search for Keystone Equities finds a web page that is empty. Using the Wayback Machine, I search for Keystone Equities in 2006 at the time of the tips, which returns Hansen's biographical sketch on the company's website. The sketch states that he is a donor to the Rochester Institute of Technology's Incubator and is a founder of Purdue University's Krannert Student Portfolio Management Program. Using this information, I am able to find his college degree information.

Finally, I use web searches to try to find any remaining data. For instance, a media article stated that two people in the data, Sandeep Goyal and Rob Ray, met in business school, but it doesn't say which school. Searching for both of their names and the word "alumni" returns an alumni donor list from the University of Texas business school showing that both donated money and lists their degrees and graduation years.

III. Summary Statistics of Events, Firms, and People

This section of the paper describes the type of events, firms, and people that are involved in insider trading.

A. Events

As mentioned above, the information that is tipped in insider trading cases are facts, not subjective opinions. For almost all cases, they are facts about a particular event, for which a firm will eventually make a specific announcement, such as a merger or earnings. In addition, the events tend to have clear positive or negative outcomes. For example, a takeover usually has a positive effect on a target's stock price. In contrast, information on a new product offering could have ambiguous effects, and so is unlikely to be shared. In a very few cases, there is no announcement date to be recorded because the firm never makes an announcement. For example, there is no public announcement when private merger negotiations fail to reach an agreement.

Table I presents the time series of the 465 events in the sample. The earliest event is 1996, and the most recent is 2013, though 89% of the events occur within 2005 to 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. There are 25 events for which I cannot identify an announcement date because the SEC and DOJ documents do not specify a specific event.

Table II presents statistics on the frequency of different types of events, stock returns, and holding periods surrounding insider trading. Panel A provides the frequency of six types of events. A detailed breakdown of the types of events is presented in Internet Appendix Table 1. The most common type of event with 239 instances, or 51.4% of all events, is a merger or acquisition (M&A). The large majority of these events are acquisitions (219), 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 events, with 123 events, or 26.4% 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.

I next characterize whether the inside information contains positive or negative news at the time the information is tipped. I base this distinction on the trading patterns of tippees: long positions and call options indicate positive news and short positions and put options indicate negative news. Almost all M&A announcements are positive news events (234 vs. 5) for the firms that are the subject of the inside information. 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. Sale of securities is overwhelming bad news in the sample with 34 negative events and one positive event. Overall, there are 335 positive events and 112 negative events. 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.

B. Stock Returns from Insider Trading

Panel B of Table II presents average stock returns for each event type. The stock returns are calculated as the return from buying stock on the date that 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 filings documents, I use the first date that the original source tips the information. Panel C presents averages of this holding period. Not all tippees earn returns equal to those in Table II 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 II 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 returns of 34.9% over 21.3 trading days. Because the returns are based on idiosyncratic inside information, there is virtually no financial risk to the strategy. There is of course, legal risk. Also, median trading periods are less at 16 days for M&A events and 10 days for all types of events.

Clinical trial and drug regulatory announcements generate the largest returns, on average, with gains of 101.2% for the 24 positive events and −38.6% for the negative events, with an average holding period of just 9.2 days. Next, 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.

The holding period averages reported in Panel C of Table II reveal that the time between learning about a future event and the actual event date is shorter for negative events than positive events. In unreported t-tests, I find that the average holding period is longer for positive news than negative news in clinical trial events (p-value$= 0.013$), M&As (p-value$= 0.002$), operations (p-value$= 0.087$), and events overall (p-value< 0.001). The difference for earnings announcements is not statistically significant. This could imply that firms delay the announcement of good news compared to bad news, or it could imply that good news travels faster than bad news.

C. Firms

Table III presents summary statistics of the firms at the event level. The sample includes 351 firms whose stocks are traded by insider traders and whose data are available on the CRSP-Compustat merged database. The missing observations tend to be small firms or foreign firms, primarily Chinese, which are traded on 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 firms, though there is wide variation across the sample. The average firm has market equity of \$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 in December 2011 has a market equity of \$1.2 billion. The 25th percentile on the NYSE is \$0.41 billion compared to \$0.30 billion for sample firms. At the the 75th percentile, NYSE firms have market equity worth \$3.45 billion compared to \$3.56 billion for sample firms. These distributions suggests that the sample firms include a representative sample of NYSE firms, plus a number of smaller firms in the left tail of the distribution.

The dollar trading volume of larger firms may be attractive for illegal insider traders because they are less likely to affect the stock price through their trades. Table III provides summary statistics of the trading volume of the firms in the sample. The median firm has a daily trading volume of about 680,000 shares and a daily dollar trading volume of \$13.08 million. There is wide variation, with some firms having very small dollar trading volumes, and others, some of the largest on the stock market.

To compare the normal trading volume of the sample firms to the illegal trading volume, Table III presents statistics on the total dollar volume of illegal trades per event. I first aggregate the total dollars invested by insider traders over all the days in the period between when the original source receives the information and the event date (21.3 days, on average; 10 days at the median). The total amount traded by tippees is \$370,000 for the median event and \$4.06 million for the average. I next calculate the total dollar amount of illegal trades divided by the firm's average daily dollar volume during a non-event period. The ratio is 6.57% at the median. Across 10 trading days, this is only 0.66% of the normal trading volume. However, at the 75th percentile, the figures are 34.56% using aggregate numbers and 3.5% at a daily level. This represents a significant fraction of the daily volume for the upper tail of insider trading activity.

Table IV presents the fraction of events by firms' industries. Compared to all firms in the CRSP database, the sample of industries represented in the illegal trading database overweights high-tech industries. Based on the size of the insider trading sample, the distribution of firms across industries in CRSP predicts that there would be about 33 insider trading events for firms in the chemical manufacturing industry, including pharmaceutical firms. In contrast, the sample includes 90 events for chemical manufacturers. Similarly, the CRSP distribution of industries predicts that firms in the computer and electronics manufacturing industry would account for 43 events. In comparison there are 91 in the sample. In contrast, the sample underweights credit intermediaries and bank holding companies.

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. Industries with many mergers just have more information, not necessarily more information leakage. However, a comparison of the industry distribution of the insider trading sample to a sample of public, US merger targets from 2004 to 2012 from SDC provides a similar result. The SDC data predict that there will be 17 merger events in the sample that involve a firm in the chemicals industry, compared to 33 actual M&A events in my sample. Similarly, software publishers are expected to account for 11 events, compared to 21 in the sample. Finally, credit intermediaries account for 15 events in the insider trading data, but are expected to account for 33 events based on the frequency of actual mergers of credit intermediaries.

These results suggest that insider trading concentrates in high-tech industries with relatively large firms with high trading volumes. As a tangible example, based on firm size, industry, and trading volume involved in the events of the sample, the median event in the sample is the acquisition of Biosite Inc. by Beckman Coulter Inc. for $1.55 billion announced in March 2007, with a premium of 53% over Biosite's price of $55.38. Both firms are biomedical firms.

D. People

There are 611 people in the data set. Of these, 155 people are tippers only, 249 are tippees only, 148 are both tippees and tippers, and 59 are original information sources who do not tip anyone else. Table V presents summary statistics of the people. The average person gives 1.5 tips, which also equals to the number of tips received by the average person since the network of tippers and tippees is closed and every tip is received by someone else in the sample. The median person gives no tips and receives one tip. In untabulated statistics, of the 155 people who only share tips, the average number of tips shared is 2.42. Of the 236 people who only receive tips, the average number of tips received is 1.94. Of the 148 who both give and receive tips, the average person receives 2.91 tips and gives 3.64 tips.

Across the entire sample, the average age of the people in the sample is 43.1 years old and 9.8% of the people are women. The youngest person is 19 years old and the oldest is 76. Figure 3 presents the geographic location of the people in the sample who are located in the United States.

Insiders 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 insiders is overweighted in California, New York, and Florida, and underweighted in Texas, Ohio, and Virginia. The sample also includes insiders located in other countries, including 16 people in China, 9 in Canada, 23 in Europe, and others from various countries including Australia, Brazil, Israel, and Thailand.

The total amount invested per tippee ranges from a minimum of $4,400 up to a maximum of $375 million. 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 are large amounts relative to the average retail investor's stock investments. This is explained partly by the composition of the types of people that receive inside information and also because people invest more money in insider trades than they normally would when the investment's return is risky. Many of the SEC complaints document that insider traders sell all of the existing assets in their individual portfolios and borrow money to concentrate their holdings in the insider trading firm.

As the stock returns documented above show, trading on inside information is highly profitable. The median investor realizes a total gains across all tips of $133,000 in ill-gotten profits and losses avoided. The average investor realizes gains of $2.3 million. Per tip, the median investor gains $72,000. The average percentage return for insider traders is 63.4% and the median is 26.4%. These returns are higher than the average event returns presented in Table II because some insiders trade stock options in addition to common stock.

Table VI presents summary statistics of insider traders by nine types of occupations. Internet Appendix Table 2 provides a detailed breakdown of the frequency of each occupation in the sample. The most common occupation among insider traders is top executive with 107 people. Of these, 24 are board members and the rest are officers. There are 51 mid-level corporate managers and 59 lower-level employees in the sample, including 8 secretaries, 11 information technology specialists, and a few nurses, waiters, and a kindergarten teacher. There are 59 people who work in the "sell side" of Wall Street including 13 accountants, 24 attorneys, 4 investment bankers, and 3 sell-side analysts. I divide the "buy side" into two groups by rank in investment firms: 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 9 engineers. There are 133 people for which I cannot identify an occupation.

Age and gender follow well-known patterns across the occupations in the sample. At 50.3 years old, top executives are among the oldest group in the sample, compared to 40.6 for mid-level managers and 40.3 for lower-level employees. Buy side managers tend to be younger than corporate executives at 41.5 years, but older than buy side analysts at 34.9, which are the youngest group in the sample, on average. Women are predominately found among lower-level employees at 25.5% and in the unknown group.

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%, though 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.

The occupations that give the most insider tips are sell side employees, such as lawyers and accountants, with 2.9 tips given, on average, and buy side analysts and traders. Buy side analysts also receive the most tips of any occupation (2.8) on average, and top executives and corporate managers receive the fewest (0.5 and 0.6). I provide a more detailed analysis of the flow of information by occupation below.

E. Summary Description of the Sample

Though there is significant variation across multiple dimensions, in general, insider traders are predominately men between the ages of 35 and 50 who work either as top executives or as buy side investors. They live all across the globe, but predominate in New York, California, and Florida.

They tend to trade on insider knowledge in advance of significant corporate events, such as mergers and earnings announcements, for firms in high tech industries. Their trades earn very large returns of about 35% over a month. These investments make large profits ($1.3 million on average per tip).

IV. Personal Relationships in the Information Networks

In this section of the paper, I present evidence on the ways in which insiders are connected to one another.

A. Social Relationships

Table VII presents the prevalence of information flows by the type of relationship between the tipper and tippee. There are 445 pairs of tippers and tippees in the sample. Of these relationships, 104 (23.4%) are familial, 156 (38.1%) are business-related, 156 (38.1%) are friendships, and 98 (24.0%) do not have any clear relationships. Multiple types of relationships are allowed. In untabulated numbers, 11 pairs of insiders have both familial and business relationships, 56 pairs of relationships are both business-related and friendships, and 4 relationships are both family and friends (typically in-laws and distant family members).

The family relationships are led by siblings (24.0% of familial relationships) and parent-child (19.2%). About 14% of the family relations are between married couples and 11.5% are through in-law relationships. The 'other' category, which includes cousins, uncles, aunt, etc, accounts for 8.7% of family relations. The 'unspecified' category (15.4% of family relationships) includes observations where the SEC and DOJ filings indicate that people in a pair are relatives, but doesn't specify the exact relationship. In unreported tests, I find that in parent-child relationships, the tipper is the parent in 30% of cases, significantly less than 50% (p-value$= 0.072$). This means that information tends to flow from child to parent.

For friendship relations, the SEC complaints commonly describe relationships as either friends or close friends, and occasionally as acquaintances. In the sample, there are just three pairs described as acquaintances, compared to 109 described as friends, and 44 described as close friends. In untabulated statistics, I verify that the distinction between friends and close friends is meaningful. In 42 relationships, the SEC complaint identifies when the relationship began, with 34 observations of friendship pairs. For the 21 friendship pairs, 6 pairs (29%) met before college, 5 (24%) met in college, 6 (29%) met in graduate school, and 4 (19%) met after they had completed their education. In comparison, among the 13 pairs of close friends with available data, 10 (77%) met before college and 3 (23%) met in college. This suggests that close friendships were formed during childhood, as might be expected. In unreported tabulations, 7 pairs of people are neighbors and 5 pairs are roommates.

Among the business-related relationships, 54.5% are among business associates. Business associates are people that work together or know each other through their profession. In comparison, boss-subordinate business relationships account for 24.4% of business-related ties and client-provider relationships account for 21.2%. 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 of the other.

The 98 pairs in Table VII where no social relationship is listed comprises a sizable number of expert networking firm relationships, where insiders 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). Thus, these are not just missing observations, but these pairs actually have no social relationships other than through sharing inside information.

The data allow me to provide a rough estimate of when relationships formed. In 50 pairs, the filings provide the time when the individuals first met. Among friendship relations, 17 of 39 pairs, or 44%, met before college, 18 (46%) met in college or graduate school, and 4 (10%) met after completing school . Among business-related pairs, 5 of 15, or 33%, met before college, 5 (33%) met during college or graduate school, and 5 (33%) met after finishing school. There is little information on when in-laws, engaged, and married couples met, so I exclude them from the calculation, leaving 70 familial pairs, all assumed to have met before college. I also ignore the 98 pairs where no social relation is listed.

Across the 124 pairs where I can estimate when the relationship began, I find that 74% met before college, 19% met in college or graduate school, and 7% met after completing their education. Since family relationships account for much of these figures, most people met during childhood. Excluding family relationships, 41% met before college, 43% met in college, and 17% met after completing school. Overall, these patterns imply that people who share inside information have long-standing and close relations with each other, on average. It also implies that the presence of school-ties are related to actual social interactions, as assumed in a number of papers (Cohen, Frazzini, and Malloy, 2010), though information is mostly shared between people who met before college.

B. Geographic Proximity in Relationships

Table VIII presents summary statistics of the geographic distance between insiders. Distance is calculated as the great circle distance in miles between the cities of the people in an information 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.

Across all pairs of insiders, 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. In unreported tests, I find no statistically significant difference in the medians of family, business, or friendship relationships. Married and dating couples live the closest to each, with a median distance of zero miles, but siblings and children live slightly further away (28 and 26.2 miles at the medians) than do business associates (16.8 miles) and clients (19.0 miles). These statistics suggest that relatively small geographic zones are reasonable proxies for a large fraction of information flows, across all types of interpersonal relationships.

Information flows are not always local, however. The 75th percentile of distance in all insider pairs is 739 miles. From New York City, this would include cities as distant as Chicago and Atlanta. At the 75th percentile for business ties, which are the lowest across the three types of relationships at 220 miles, business relations in New York City would include people in Washington D.C., Philadelphia, and Boston. This means more that a substantial fraction of relationships are distant.

The distant geographic relations follow particular patterns. Figure 4 shows the information flows across the US. There are strong links between New York City and the Miami area, between New

York and the San Francisco Bay area, and between Southern and Northern California. These are not surprising, as New York and Los Angeles are the two largest metropolitan areas in the US. However, Chicago, Dallas, Houston, and Atlanta, which are the third, fourth, fifth, and ninth largest metropolitan areas are underrepresented compared to the Miami area which is eighth in terms of population size.

C. Directionality in Tipping Relationships

Figure 5 provides a heat map of the connections between tippers and tippees by occupation. These relations are based on binary connections between people, not the total number of tips, 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 figure shows that top executives are the most frequent tippers with 100 pairs comprising top executive 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 (11%), and managers (10%), and all other occupation categories in the sample. In contrast, buy-side managers are the next most common tippers with 88 pairs, but their tippees are concentrated among buy side managers (33% of their tippees) and buy side analysts (22%).

The heat map provides an indication of the direction of information flow. First, the strong diagonal pattern in the figure shows that tipping relationships tend to concentrate among people in the same occupations. Buy side managers and analysts tend to tip other buy side managers and analysts. Sell side employees tend to tip other sell side employees, and top executives tend to tip other top executives. Comparing the number of pairs in which a particular occupation is a tippee compared to a tipper, shows that top executives are roughly three times more likely to be a tipper than a tippee. There are 2.35 times more pairs where a corporate managers is a tipper than a tippee. In contrast, buy side analysts are tippees in roughly twice as many pairs as they are tippers. Pairs with small business owners and specialized occupations as tippees are roughly 1.4 times more common than pairs in which they are tippers.

In untabulated results, I test whether subordinates are more likely to tip supervisors or vice versa. A subordinate may tip his boss in order to advance his career. Similarly, a service provider may have an incentive to tip his client. In 63% of boss-subordinate relationships the tipper is the subordinate, a significant difference from 50%. In 55% of client-provider relationships, the tipper is the provider, which is not significantly different than 50%. These results imply that information flows in both directions equally between clients and their agents, but disproportionately from subordinates to bosses.

Figure 6 presents a similar analysis by age of tipper and tippee. At the aggregate level, there is a strong negative relation between age and the number of tipping relationships for both tippers and tippees. Tippers between the ages of 30 to 34 have the most tipping relations, which then decline as tipper age increases. Similarly, tippees who are between 30 to 34 have the most relations which then decline as tippees get older. The strong diagonal component of the figure reveals that tippers and their tippees tend to be close in age. Of the 64 tippee-tipper age groups in Figure 6, 37% of all pairs are found in the eight groups where tippers and tippees are the same age. In the off-diagonal regions, there are more relationships where younger tippers are sharing information with older tippees than vice versa (89 pairs versus 70 pairs).

In untabulated statistics, I find that men and women tend to form tipping relationships with each other. When the tipper is a man, 9% of relationships are with female tippees. Instead, when the tipper is a woman, 14% of relations are with female tippees. When the tippee is a man, 10% of tippers are women, and when the tippee is a woman, 16% of tippers are also women.

D. Summary of Pair-Level Relationships

The statistics in this section reveal a detailed picture of tipper-tiee relations. Tippers and tippees are not randomly matched. They tend to have strong social connections through family, friendships, and professional interactions. A majority of people in tipping relationships met each other before college. Siblings are the most common family relationships among inside traders, but when parents and children tip each other, information is more likely to flow from children to parents. Professional relationships are typically between business associates, rather than bosses and clients. When bosses and subordinates share information, the information typically flows from the subordinate to the boss. Similarly, tippers and their tippees tend to be close in age, but tippers tend to be younger than their tippees. People also tend to tip other people in their same occupation, though top executives tip people of all occupations. Finally, tippers and tippees live close to each other, suggesting that face-to-face social interaction is associated with information sharing.

V. The Diffusion of Information Across the Network

In this section of the paper, I trace out the path through which information flows from the original source to the final tippee.

A. Original Sources

The original source of an insider trading event differs based on the event. I break the sample of events into the major types of events: M&As, earnings news, and everything else. Table IX presents statistics on the original sources of M&A events.

The original source in an M&A obtains the information through connections with the acquirer, the target, or a third party. Since the same M&A event can have multiple sources, there are 285 original sources of M&A events. Of the total original sources in M&As, 99 (35%) original sources are associated with the acquirer, 119 (42%) with the target, and the remaining 67 (23%) with a third party or an unknown party. Sources can also be classified as internal or external. Internal sources include employees of the acquirer or target. External sources include employees of firms that contract with the acquirer or bidder, such as accounting firms, investor relations firms, investment banks, and law firms. In M&As, 117 of the 285 original sources (41%) are internal sources, compared to 164 external sources (58%). Internal acquirer leaks are evenly split between officers and lower-ranked employees, with no leaks from acquirer directors. In contrast, target officers are responsible for 48% of leaks, target directors for 29%, and lower-ranked employees for 23% of internal leaks from the target.

The most common type of firm where external leaks occur in M&As is a law firm, accounting for 40% of all external sources. Investment banks are the next most common (23%), followed by accounting firms (13%). For many external sources, there is an even balance between sources associated with the target and those associated with bidder. However, accounting firms working for an acquirer account for 2.5 times as many sources as accounting firms working for the target. In contrast, target law firms account for twice as many leaks as acquirer law firms. Finally, a substantial number of leaks are stolen (about 18% of all external sources). These are cases where a friend or family member secretly accesses information. For instance, a merger attorney's father misappropriated confidential information from his daughter's work documents while she visited him during holidays (see SEC v. Dean A. Goetz). These statistics reveal that insider news about M&A come from a wide range of sources, both internal and external.

Tips about earnings announcements are either internal or external to the announcing firm. These data are presented in the last column of Table IX. In contrast to M&As, lower ranked employees of the firm are the most common internal source of the information. These employees account for 52% of all internal sources, compared to directors, which account for 5%. Another difference between M&A sources and earnings sources is that earning sources are predominately internal (67%) compared to external (31%). Not surprisingly, the most common external source is an accounting firm, followed by investor relations firms. There are five tips in the sample where an employee at the Market Intelligence Desk of the NASDAQ received advanced notice of earnings releases for NASDAQ listed firms.

Internet Appendix Table 3 presents the original source of information in the remaining event types. Most of these sources are external to the firm. In particular, in 34 events, an employee of a potential investor or bidder in a failed merger is the original source. In 27 cases, a regulatory agency employee receives inside information, typically about drug approvals or clinical trial updates.

B. Tip Chains

Insider information follows a path from the original source to other tippees. I denote a "tip chain" as the ordering of people who are tipped as the information flows from the original source to others. The order in the tip chain is the number of links from the original source. If a tipper tips multiple tippees, than each of these tippees is in the same order in the tip chain. The first order in the tip chain is the connection between the original source and his tippees. By identifying these orderings, we can better understand the path through which information flows between insiders.

Table X presents the occupations of tippers and tippees by their order in the tip chain. Tippers in the first link are the original sources. Top executives (34%) make up the largest component of original sources followed by sell side employees (26.3%) and then lower-level employees (16.1%) and corporate managers (13.7%). Buy side managers and analysts are very rarely original sources (1.0% and 1.9%). The tippees in the first link from the original source are most commonly buy side analysts (19.3%), followed by buy side managers (12.5%). The rest of the tippees in the first link are evenly spread across all occupations. These results are consistent with the heat maps of the inter-occupation information flows shown previously.

As information progresses across the tip chain, a number of patterns emerge. Officers become less common tippees, going from 9.2% of all tippees in the first link to 0% of tippees in fourth and subsequent links. Corporate managers, lower-level employees, and people in specialized occupations follow the same decreasing pattern. Insiders in these roles are much more likely to receive the information from an original source than an intermediary. In contrast, buy side managers and analysts are increasingly the tippees as the information travels further from the source, accounting for 34.5% and 25.5% of all tippees in the fourth and subsequent links. On the other side of the tipping relationship, Table X shows that as information flows further from the original source, buy side managers and traders are tipping other buy side traders. Executives, corporate managers, lower-level employees, small business owners, and specialized workers are all becoming less likely to be tippers as the tip moves further from the original source.

Internet Appendix Table 4 presents a similar analysis of occupations across the tip chain, for long versus short tip chains. The distribution of original sources is highly similar in long and short tip chains. In longer tip chains, the first tippees are more likely to be buy side traders than corporate executives and managers. In shorter tip chains, corporate executives and managers are more likely to be the first tippee compared to buy side traders. Compared to the same link in the tip chain, the later tips in short chains tend to go to executives and sell side employees, whereas they go to buy side traders in longer chains. These results suggest that there is a path-dependence based on the earliest tippees. When early tippees are buy side traders, the tip chain is longer and few corporate employees and sell side workers receive the information. When the early tippees are corporate and sell side workers, the tip chain is shorter and buy side traders are less likely to receive the information.

These patterns show that information travels from corporate insiders through various intermediaries and eventually reaches professional traders who then share the information among themselves. The intermediary links include a wide variety of occupations, such as managers and officers other than the source, lawyers, specialized occupations, and investment bankers and analysts. It takes at least three links before professional buy side traders dominate the information exchange.

Table XI presents additional information about the characteristics of tippers and tippees along the tip chain. Tippees are women in 8.1% of first tips, declining to 2.5% in fourth and later links in the tip chain.[3] This probably reflects that compared to other professions, women are underrepresented among buy side managers and analysts. Tippers and tippees become younger as the information flows further from the original source. In the first link, tippees are 41.8 years old on average, declining to 37.5 by the fourth and subsequent links. The average tipper's age declines from 42.5 years to 33.7 years old.

There are also clear patterns of social connections over the tip chain. Tippers and tippees are primarily friends (42.2%) and family members (25.1%) in the first link of the tip chain and then steadily decline as the tip moves further from the source to 20.0% for friendship connections and 12.7% for family connections by the fourth and later links. In contrast, business connections grow in prevalence from 28.9% in the first link to 63.6% by the fourth and later links. Geographic distance follows a hump-shaped pattern over the tip chain. Tippers and tippees live further away from each other in the second link than they do in the first, but by the fourth and later links, distance has declined to zero at the median, which indicates that the median tippers and tippees live in the same city.

C. Trading Characteristics over the Tip Chain

Table XI 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

[3]The jump to 17.3% for women in the third link in the tip chain is driven by one set of serial inside traders.

tip. However, trading returns decline over the tip chain, indicating that the information is moving stock prices. 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. As the trade sizes get larger, the fraction of total trading volume accounted for by insiders increases. 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 XI presents evidence on the speed of the information flow over the tip chain. 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 holding 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.

Finally, Table XI shows the network centrality of the tipper and tippee over the tip chain. Centrality is measured as the number of tipping links a person has to all other people. More central people have more information connections with others. The table shows a quick increase in the centrality of the tipper over the tip chain. In the first link, the average tipper has 2.9 information connections. In the second link, the tippers' average degree centrality increases to 4.3. By the fourth link, the tipper has a degree centrality of 4.6. In contrast, the tippee's centrality decreases from 2.9 in the first link to 1.8 by the fourth and subsequent links. This pattern implies that tippers in later links are more central figures that are spreading the information to peripheral people in the network. I explore these relations in more detail in the next section of the paper.

Because many of the characteristics of inside traders are correlated, Table XII presents regression results where the dependent variable is the position in a tip chain and the independent variables are tipper and tippee characteristics. Columns 1 and 2 present OLS regression coefficients. Columns

3 and 4 present ordered logit regression coefficients. The results indicate that age is negatively related to a tipper's position in the tip chain, even after controlling for occupation, gender, and distance. Family and friends relationships decline with order in the tip chain, even after controlling for occupation. Likewise, the presence of buy side tippers are positively related with distance from the original source in a tip chain, compared to top executives, after controlling for age, gender, and the type of relationship.

D. Summary of the Diffusion of Information

The results in this section of the paper reveal distinct patterns in the diffusion of inside information. Original sources of M&A information are most commonly top executives of firms, and the original source is equally likely to be an employee of the acquirer, the target, or an outside firm. In contrast, lower level employees are more likely to leak earnings news than are top executives. As information diffuses from the original source, top executives and mid-level corporate managers are less likely to share information. Instead, buy side investors become dominant after three degrees of separation from the original source, with family and friend relationships declining over the tip chain and professional relations increasing. Investors invest larger sums, earn lower returns, share information faster, and have shorter holding periods as information moves away from the original source.

VI. Networks of Inside Traders

In the final section of the paper, I investigate the networks of inside traders. The entire sample of people and their connection could be considered one network. However, within this network, there exist many connected components. A connected component is a portion of the network in which all the people in the component are connected to each other through direct or indirect links. For example, if a tipper and a tippee are only connected to each other and no one else, then they form a connected component. For simplicity, I refer to these as insider networks.

Within the entire sample there are 184 insider networks. There are 59 networks that contain only one person. These are people who obtained inside information and did not tip it to anyone else. The remainder of the size distribution of the networks is as follows: 60 networks with 2 members, 18 networks with 3 members, 18 networks with 4 members, 12 networks with 5 or 6 members, 11 networks with 7 to 10 members, and 6 networks with more than 10 members.

The largest connected network centers on Raj Rajaratnam and is discussed as an illustration in the introduction of the paper (see Figure 1). The second largest network, shown in Figure 7, centers on traders affiliated with the expert networking firm, Primary Global Research (PGR), and the hedge funds owned by SAC Capital. The SAC-PGR network has 46 members with a few key players. In the bottom left of the figure are Danny Kuo and Jesse Tortora, a buy side manager and analyst. In the top right is James Fleishman, a PGR employee and Mark Longoria, a mid-level manager in Advanced Micro Devices.

Following the direction of information flow in the figure reveals that the center of the network is Steven Cohen, who oversees a number of large hedge funds owned by SAC Capital. Cohen receives information from five different sources, three of which have multiple sources of information themselves. While Cohen receives information from many sources, he does not tip anyone else. Other large networks are presented as examples in Figures 8, 9, and 10.

Table XIII presents summary statistics of personal characteristics, social connections, trading activity, timing of information flows, and trading behavior by the size of insider networks. The density of the network is the proportion of all possible connections that actually exist. As networks grow in size, they become less connected. For networks with six or more members, only 20% of possible information connections actually exist. The diameter of the network is defined as the longest of all shortest paths between any two members. In the sample of networks, the diameter of a network increases as more members are added. This provides additional evidence that networks become more dispersed and sprawling, instead of compact and closely tied to a central hub. The average clustering coefficient is a measure of how closely connected is the average node in a network. A node's clustering coefficient is the fraction of a node's links that are also linked to each other. In the sample of insider networks, the average clustering coefficient is also decreasing. These network statistics reveal that as a network gets larger it is spreading out from its outer members. The Rajaratnam and SAC-PGR networks illustrate this phenomenon.

Next, as networks increase in size, they have a smaller fraction of female tippers, which means that women tend to be tippers in small networks. The age of tippers and tippees also decrease with network size. Younger insiders tend to be included in large networks. Also, as networks grow, there exist fewer family connections and more business connections. Friendship connections remains roughly the same across network size. Given that family sizes are limited, this is not surprising. The median geographic distance 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.

VII. Conclusion

This paper provides new evidence on the spread of information in financial markets using detailed data from illegal insider trading cases. In particular, the paper provides new answers to basic questions such as who shares information with whom, what type of information is shared, who is the original source, how are these people related, and how fast does information travel?

The results show that original sources of inside information are varied, but top executives are the most common. They tend to share information with other top executives first. The information then typically proceeds through a number of links and ends up with buy side analysts and managers. Information tends to flow from younger people to older people, from children to parents, and from subordinates to bosses. 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. Tippers and tippees tend to live close to one another geographically, but there is wide variation, as insiders reside all over the globe. Networks of inside traders are sprawling, rather than centralized, where larger networks are more likely based on business relationships than family or friends.

The results of this paper provide a groundwork for existing research and suggests new directions for future research. First, the results validation for proxies of social interaction used in existing papers: geographic proximity (e.g., Brown, Ivković, Smith, and Weisbenner, 2008) and common educational backgrounds (e.g., Cohen, Frazzini, and Malloy, 2010). Second, the paper shows that social connections 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 the role of social interactions in financial decision-making, which Hirshleifer (2014) calls "social finance."

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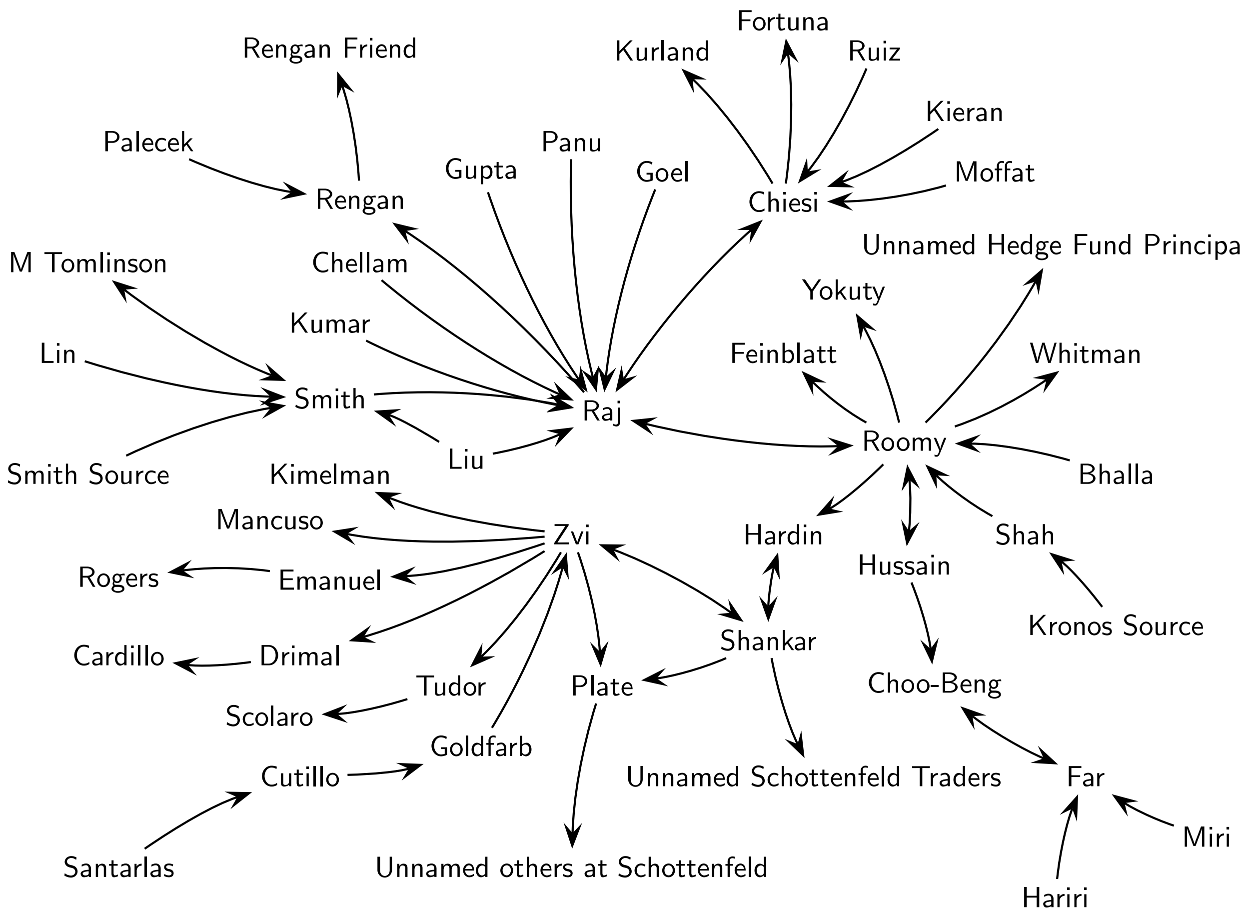

Figure 1
Raj Rajaratnam Network
This figure represents the illegal insider trading network centered on Raj Rajaratnam. Arrows represent the direction of information flow. Data are from SEC and DOJ case documents, plus additional source documents to identify individuals not named in the SEC and DOJ documents.

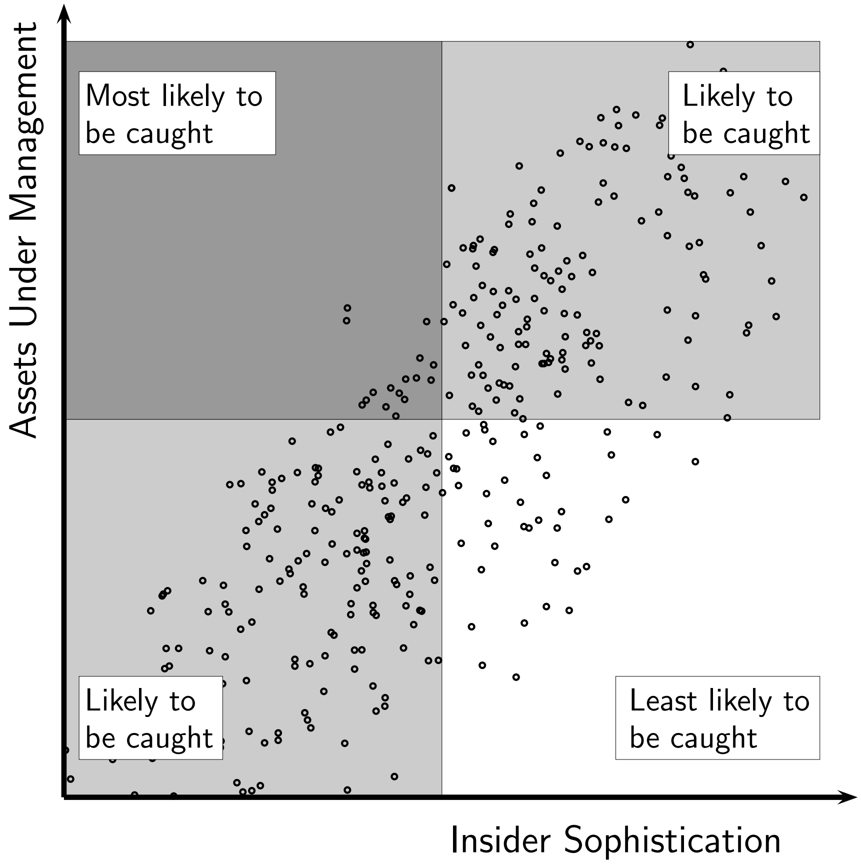

Figure 2
Stylized Illustration of Selection Bias
This figure represents a stylized illustration of potential selection bias in the sample of illegal insider trading cases. The circles represent the population of inside traders. Circles higher on the y-axis are insiders with more assets under management. Circles further to the right on the x-axis are more sophisticated traders. Sophistication and assets under management are assumed to be positively correlated, though there are more sohisticated investors with smaller amounts of assets than there are unsophisticated investors with large amounts of assets. Regulators are more likely to detect insider trading when inside traders are less sophisticated and when inside traders have more assets under management. The majority of cases are equally likely to be detected by regulators, but sophisticated insiders with small amounts of assets are underrepresented in the sample of insider trading cases.

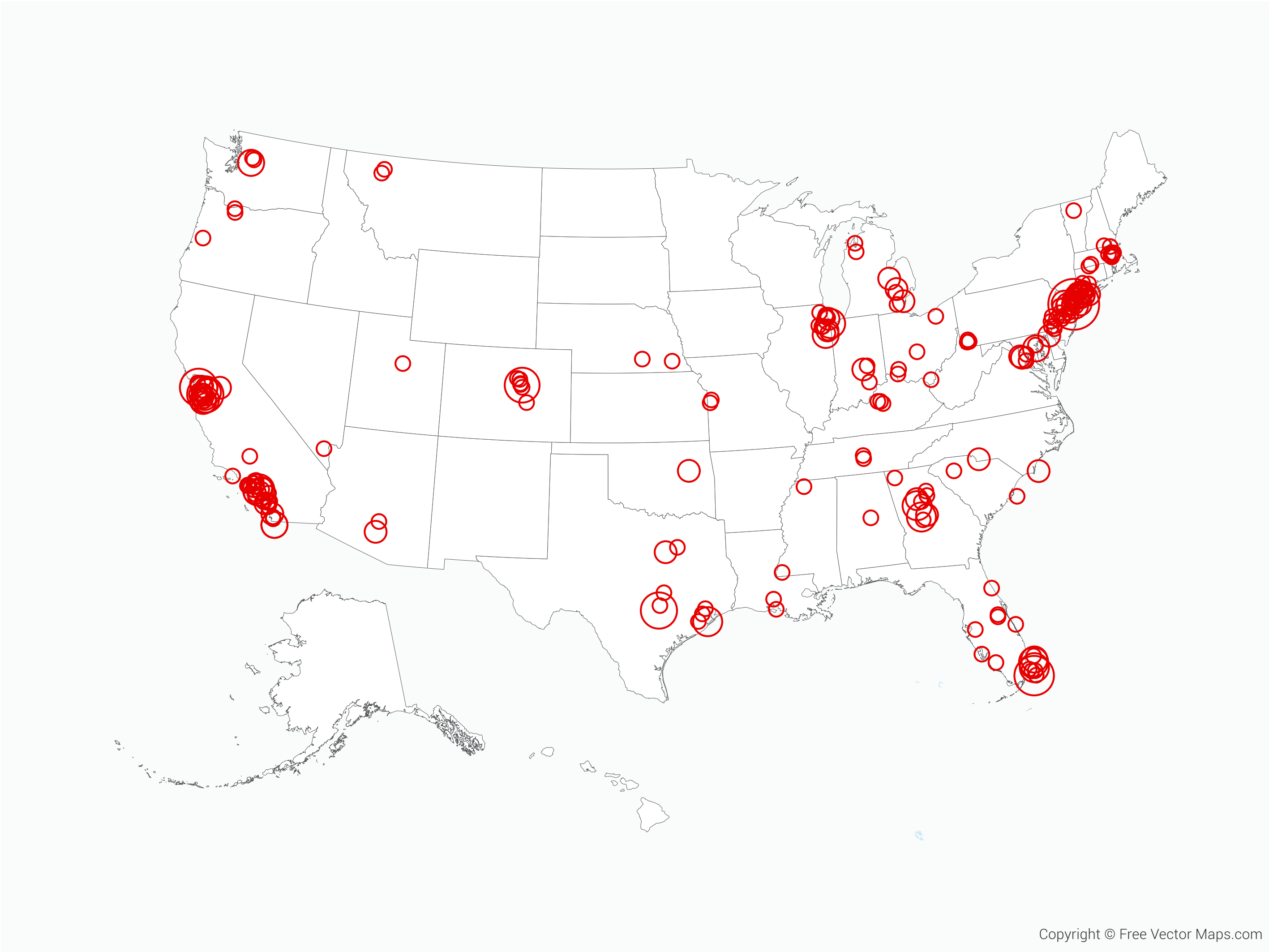

Figure 3
Location of Tippers and Tippees

Larger circles represent cities with more tippers and tippees.

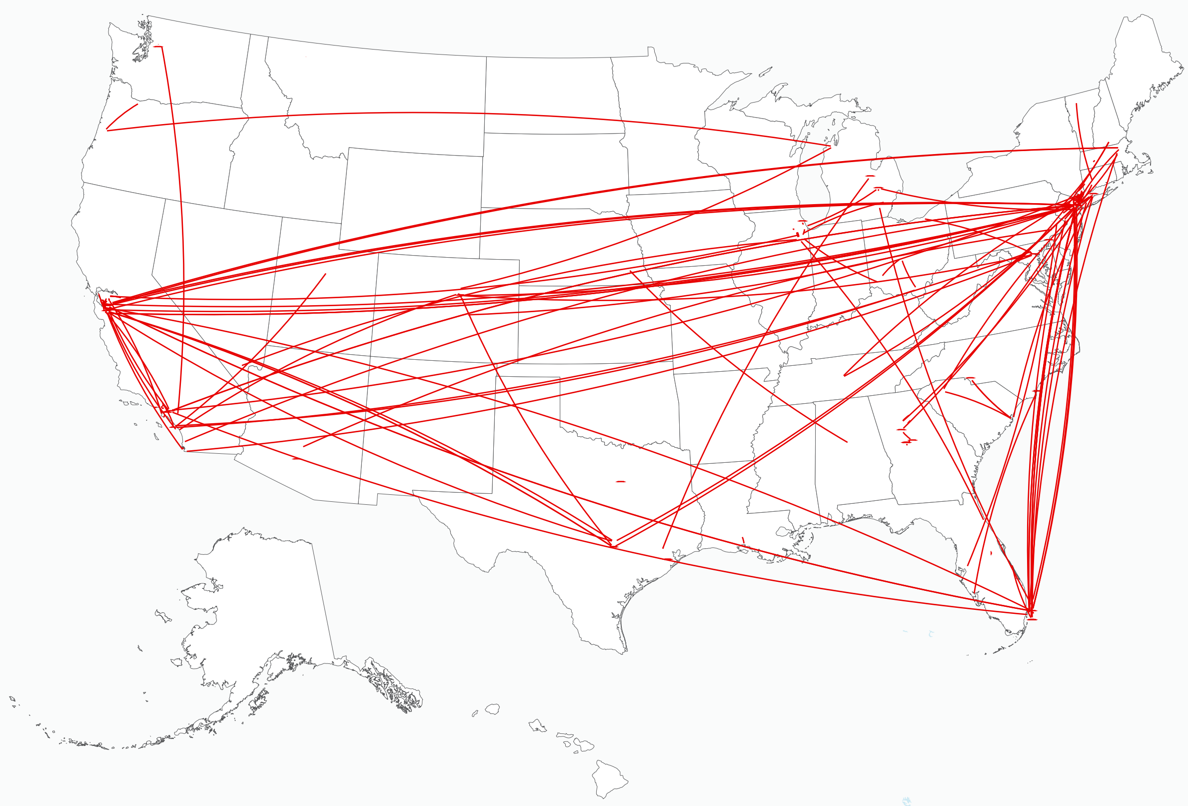

Figure 4
Tipper-Tippee Links

This figure shows the links between tipper and tippees by city. Intra-city links are not shown.

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**	**10**	**11**	**9**	**13**	**100**
Corporate managers	**6**	**5**	**2**	**2**	**6**	**10**	**3**	**1**	**40**
Lower-level employees	**3**	**2**	**8**	**1**	**2**	**5**	**10**	**5**	**45**
Sell side	**1**	**1**	**4**	**12**	**10**	**3**	**8**	**1**	**46**
Buy side: managers	**4**	**0**	**6**	**4**	**29**	**19**	**2**	**2**	**88**
Buy side: analysts	**1**	**2**	**3**	**0**	**8**	**24**	**0**	**0**	**44**
Small business owners	**1**	**0**	**3**	**4**	**2**	**1**	**3**	**1**	**29**
Specialized occupations	**1**	**0**	**0**	**2**	**1**	**8**	**2**	**2**	**21**
Total	**35**	**17**	**38**	**36**	**75**	**85**	**41**	**30**	**460**

Figure 5
Number of Connections between Tipper-Tippee 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. Occupation definitions are detailed in Table 2.

Tipper Age \ Tippee Age	≤29	30–34	35–39	40–44	45–49	50–54	55–59	≥60	Total
Total	**25**	**46**	**44**	**44**	**33**	**27**	**13**	**20**	**252**
≥60	**1**	**2**	**1**	**1**	**0**	**2**	**1**	**6**	**14**
55–59	**0**	**1**	**1**	**0**	**5**	**3**	**3**	**2**	**15**
50–54	**2**	**0**	**3**	**4**	**2**	**2**	**2**	**2**	**17**
45–49	**3**	**2**	**5**	**7**	**14**	**10**	**1**	**3**	**45**
40–44	**0**	**5**	**2**	**16**	**5**	**1**	**1**	**1**	**31**
35–39	**3**	**7**	**20**	**9**	**3**	**1**	**0**	**2**	**45**
30–34	**7**	**23**	**11**	**7**	**2**	**6**	**4**	**3**	**63**
≤29	**9**	**6**	**1**	**0**	**2**	**2**	**1**	**1**	**22**

Figure 6
Number of Connections between Tipper-Tippee 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. Totals include connections to people with unknown ages, so row and column sums do not add up to the totals.

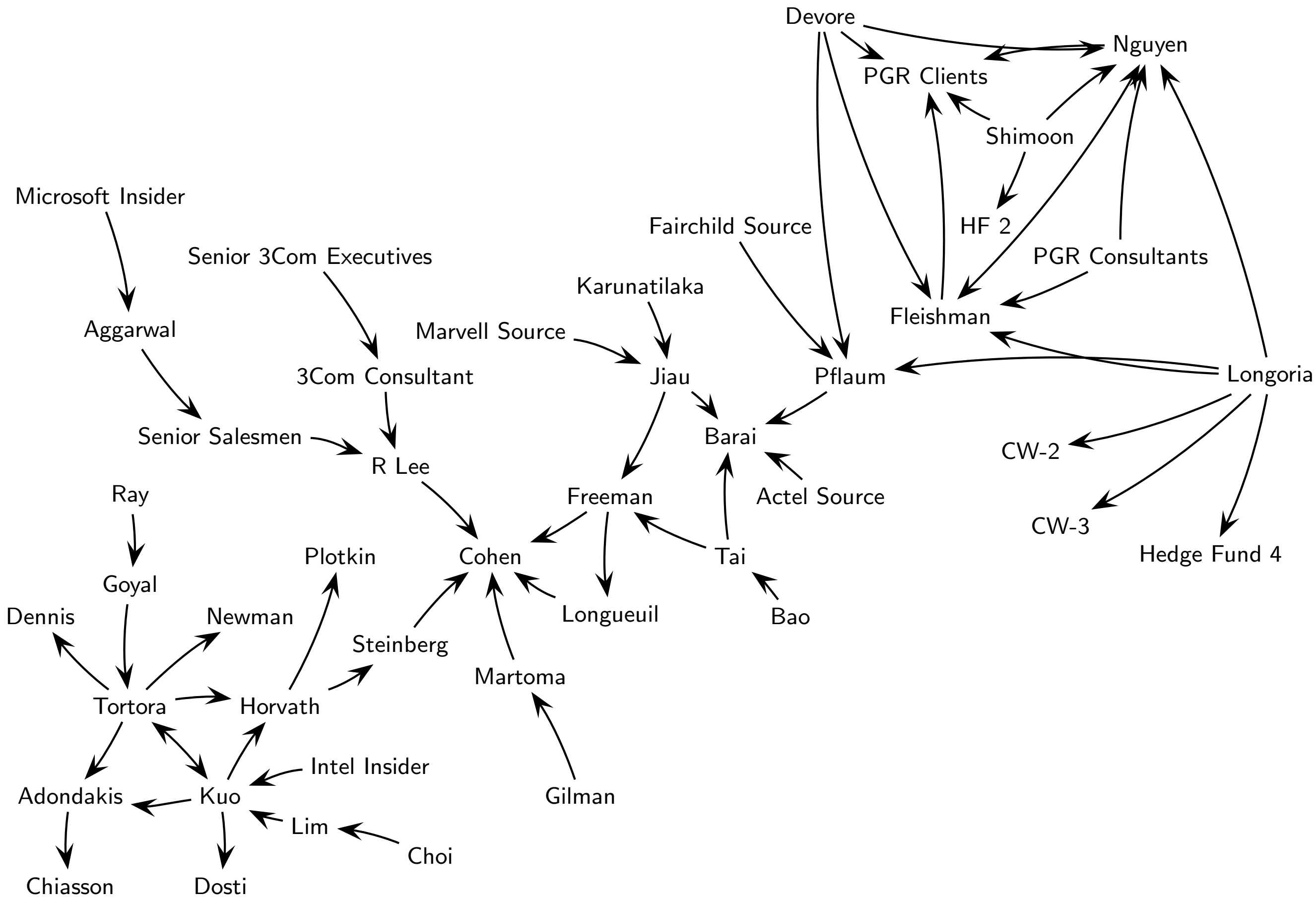

Figure 7
SAC-PGR Network
This figure represents the illegal insider trading network centered on the hedge funds controlled by SAC Capital and the expert networking firm, Primary Global Research. Arrows represent the direction of information flow. Data are from SEC and DOJ case documents, plus additional source documents to identify individuals not named in the SEC and DOJ documents.

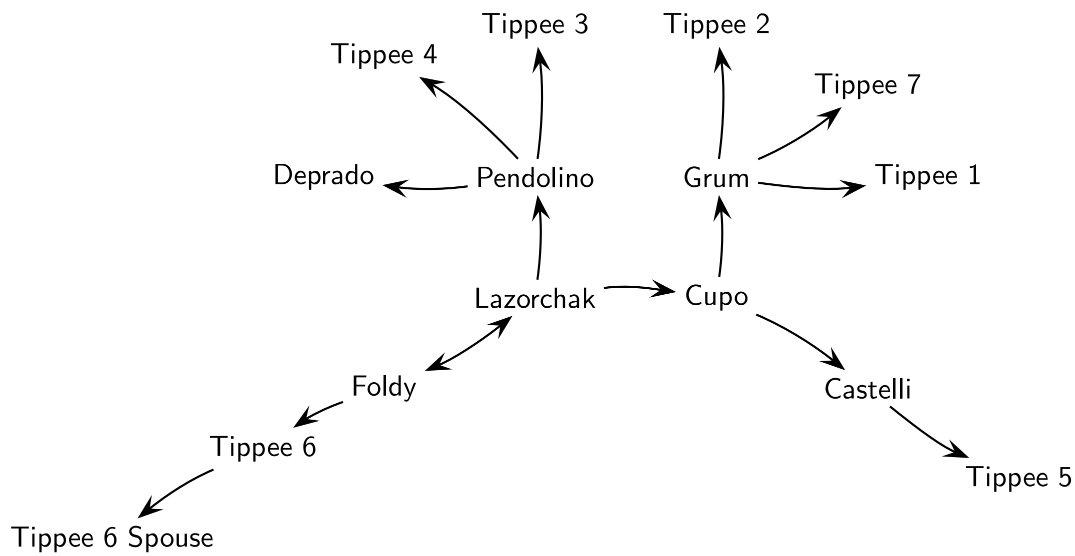

Figure 8
Lazorchak-Foldy Network
This figure represents the illegal insider trading network centered on John Lazorchak and Mark Foldy who shared inside information with others. Arrows represent the direction of information flow. Data are from SEC and DOJ case documents, plus additional source documents to identify individuals not named in the SEC and DOJ documents.

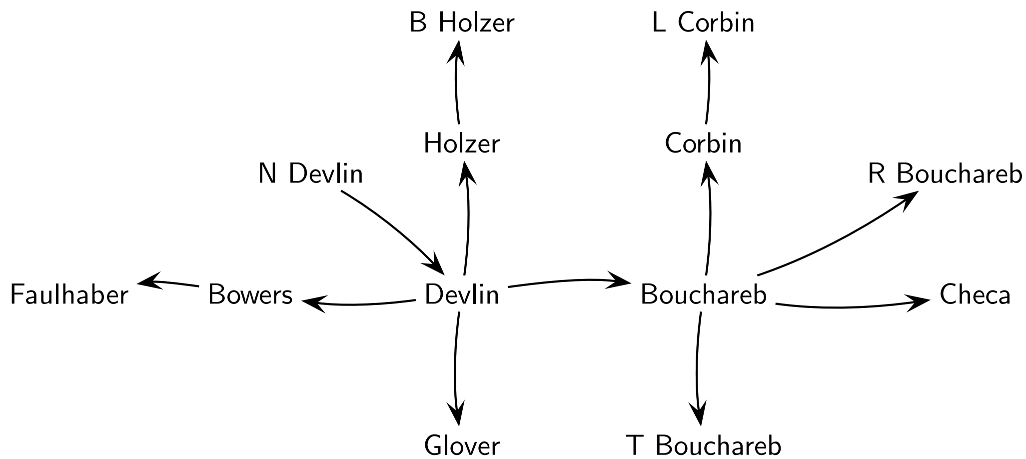

Figure 9
Devlin Network
This figure represents the illegal insider trading network centered on Matthew Devlin who received inside information from his wife, Nina Devlin. Arrows represent the direction of information flow. Data are from SEC and DOJ case documents, plus additional source documents to identify individuals not named in the SEC and DOJ documents.

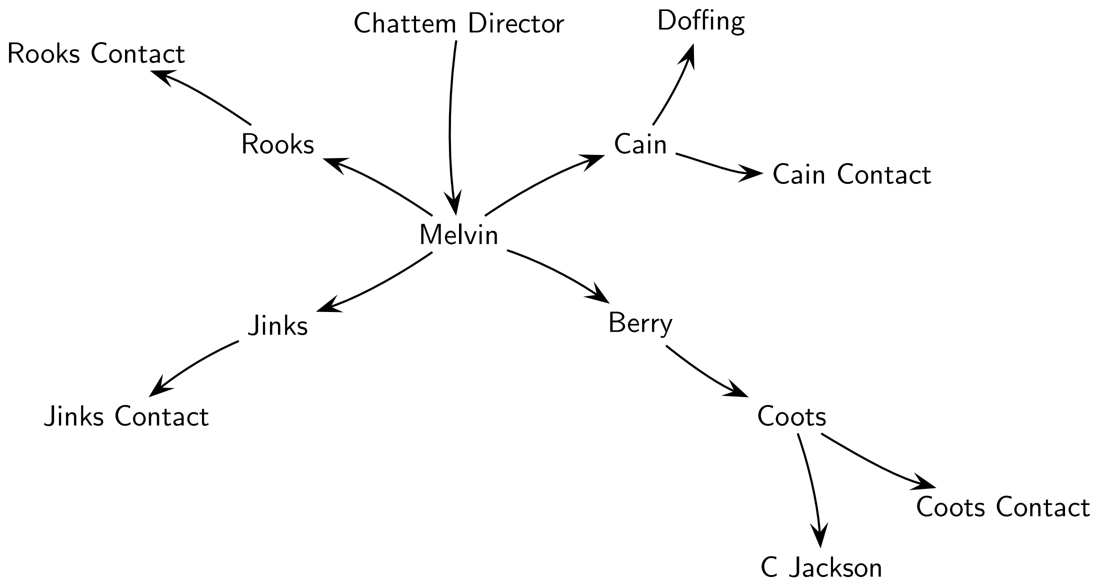

Figure 10
Melvin Network
This figure represents the illegal insider trading network centered on Thomas Melvin who shared inside information from an unnamed Chattem Director with others. Arrows represent the direction of information flow. Data are from SEC and DOJ case documents, plus additional source documents to identify individuals not named in the SEC and DOJ documents.

Table I
Events by Year
This table provides a breakdown of the years of the corporate events in the sample. The data include 465 corporate events over the years 1996 to 2013 from SEC and DOJ case documents.

Year	Number of Events	Fraction
1996	1	0.2
1997	6	1.3
1998	8	1.7
1999	0	0.0
2000	0	0.0
2001	1	0.2
2002	1	0.2
2003	0	0.0
2004	4	0.9
2005	18	3.9
2006	47	10.1
2007	69	14.8
2008	81	17.4
2009	76	16.3
2010	66	14.2
2011	40	8.6
2012	17	3.7
2013	5	1.1
Unknown	25	5.4
Total	465	

Table II
Corporate Events and Returns
This table presents the frequency (panel A), stock returns (panel B), and timing (panel C) of illegal insider trading events. The data include 465 corporate events over the years 1996 to 2013 from SEC and DOJ case documents. Frequency of events in panel A are the number of occurrences of an event type. Stock returns in panel B are the average raw stock returns from the date that the original tipper receives the information through the date of the corporate event. Panel C presents the average number of trading days between the date that the original tipper receives the information through the date of the corporate event. "Negative", "Positive", and "Unknown" columns indicate the expected effect on stock prices, based on the trading behavior of tippees. Stock returns in the "All" column are calculated as long positive events and short negative events. Detailed descriptions of each event type are presented in the appendix.

	Outcome			
Event Type	Negative	Positive	Unknown	All
Panel A: Frequency of events				
Clinical Trial/Drug Regulation	13	24	0	37
Earnings	54	66	3	123
M&A	5	234	0	239
Operations	3	8	2	13
Sale of Securities	34	1	0	35
Other	3	2	13	18
Total	112	335	18	465
Panel B: Information to event returns (%)				
Clinical Trial/Drug Regulation	−38.6	101.2		79.7
Earnings	−12.2	14.7		13.5
M&A	−20.3	43.7		43.1
Operations	−29.7	22.9		24.9
Sale of Securities	−12.8	0.0		12.8
Other	−28.9	−4.8		8.9
Total	−16.8	42.4		34.9
Panel C: Information to event time (trading days)				
Clinical Trial/Drug Regulation	5.3	11.2		9.2
Earnings	10.2	12.3		11.3
M&A	7.8	31.1		30.5
Operations	2.0	7.9		6.1
Sale of Securities	11.1	5.0		10.9
Other	101.1	3.0	1.3	44.3
Total	12.2	25.0	1.3	21.3

Table III
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 to 2013. "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. "Invested/Daily dollar volume" is total dollars invested by tippees divided by daily dollar volume. This means the amount invested is the aggregate trading by insiders over many trading days relative to an average day of normal trading activity.

				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
Invested/Daily dollar volume (%)	45.96	153.11	0.02	1.31	6.57	34.56	2011.43	259

Table IV
Events by Industry
This table presents the frequency of illegal insider trading events by two-digit NAICS level industry definitions, using data from 465 corporate events over the years 1996 to 2013. “Example firms in sample” presents non-exhaustive lists of sample firms for each industry definition.

Industry	Number of events	Fraction of total	Example firms in sample
Computers and electronics	91	23.1	Dell, Intel, Nvidia, Sun Microsystems
Chemical manufacturing	90	22.8	Celgene, MedImmune, Pharmasset, Sepracor
Food and apparel manufacturing	40	10.2	Carter’s, Green Mountain Coffee Roasters, Smithfield Foods
Information	39	9.9	Akamai, Autodesk, Clearwire, Google, Microsoft
Finance and insurance	27	6.9	East West Bancorp, Goldman Sachs, Mercer Insurance Group
Professional and technical services	20	5.1	Alliance Data Systems, F5 Networks, Perot Systems
Wholesale trade	18	4.6	Herbalife, InVentiv Health, World Fuel Services
Mining and oil extraction	13	3.3	Delta Petroluem, Mariner Energy, Puda Coal
Retail trade	12	3.0	Albertson’s, Best Buy, J. Crew, Walgreen Company
Health care	8	2.0	Humana, LCA Vision, Option Care
Real estate	8	2.0	Bluegreen Corporation, Mitcham Industries
Administrative support	8	2.0	Comsys IT Partners, DynCorp International, PeopleSupport
General merchandise stores	6	1.5	Barnes & Noble, Office Depot, Sears
Transportation	4	1.0	Airtran Holdings, K-Sea Transportation Partners
Accomodation and food services	4	1.0	CKE Restaurants, Hilton, Rubio’s Restaurants
Utilities	2	0.5	SouthWest Water Company, TXU Corp.
Construction	2	0.5	Complete Production Services, Warrior Energy Services
Education	1	0.3	Global Education and Technology Group Limited
Other	1	0.3	Berkshire Hathaway Inc.

Table V
Summary Statistics of People Involved in Insider Trading
This table presents summary statistics of age, gender, tipping activity, investment, and returns for the 611 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. "Tips given" is the number of insider trading tips given to others. "Tips received" is 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" is 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
Age	43.1	11.3	19.0	34.5	41.0	50.4	76.0	410
Female (%)	9.8	29.8	0.0	0.0	0.0	0.0	100.0	488
Tips given	1.5	3.2	0.0	0.0	0.0	1.0	29.0	611
Tips received	1.5	2.5	0.0	0.0	1.0	1.0	24.0	611
Total invested ($1,000s)	4,288.0	25,334.9	4.4	74.5	226.0	1,116.2	375,317.3	255
Average invested per tip ($1,000s)	1,690.3	6,088.6	4.4	65.0	200.0	701.4	72,427.5	255
Total gains ($1,000s)	2,333.3	13,194.8	0.9	34.2	133.0	606.0	139,000.0	398
Average gains per tip ($1,000s)	1,301.4	10,064.3	0.1	20.6	72.0	285.1	139,000.0	398
Average return (%)	63.4	231.8	0.0	14.0	26.4	46.5	3347.3	255

Table VI
Summary Statistics by Occupation
This table presents averages of age, gender, tipping activity, investment, and returns by occupation for the 611 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 V defines the variables. Table 2 presents a breakdown of occupations into narrower categories.

Occupation	Count	Percent	Age	Female	Tips Given	Tips Received	Median invested per tip ($1,000s)	Median gains per tip ($1,000s)	Median Return
Top executive	107	17.5	50.3	6.1	1.5	0.5	376.8	2,903.0	33.7
Corporate manager	51	8.3	40.6	6.0	1.7	0.6	1,973.3	286.0	71.8
Lower-level employee	59	9.7	40.3	25.5	1.7	1.5	558.3	149.3	47.5
Sell side: lawyer, accountant, i-bank	59	9.7	40.7	9.6	2.9	1.8	3,756.5	254.7	58.8
Buy side: manager	60	9.8	41.5	6.4	1.4	2.6	5,971.7	5,834.7	37.0
Buy side: analyst, trader	65	10.6	34.9	5.2	2.6	2.8	2,051.2	451.1	117.7
Small business owner	39	6.4	46.2	5.3	0.9	2.3	203.9	196.5	62.0
Specialized occupation	38	6.2	51.2	2.8	1.2	1.6	598.5	234.4	32.8
Unknown	133	21.8	39.1	20.8	0.5	1.1	583.6	354.6	77.0

Table XII
Tip Chain Position Regressions
This table presents OLS regressions (columns 1 and 2) and order logit regressions (columns 3 and 4) where the dependent variable is the position in the tip chain, where the variable equals one if the observed tipping relationship is the first link from the original source, two if it is the second link from the original source, and so on. The omitted benchmark occupation for tippers and tippees is "Top executive". Heteroskedaticity-robust p-values are reported in parentheses. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

	OLS		Ordered logit	
	Dependent Variable: Position in Tip Chain			
	(1)	(2)	(3)	(4)
Tippee is female	0.204	0.232	0.559*	0.809
	(0.133)	(0.108)	(0.099)	(0.079)
Tipper is female	0.061	−0.163	0.415	0.134
	(0.562)	(0.214)	(0.107)	(0.767)
log(Tippee age)	−0.278	0.359*	−0.921*	0.414
	(0.156)	(0.069)	(0.060)	(0.561)
log(Tipper age)	−0.867***	−0.590***	−2.062***	−2.270***
	(< 0.001)	(0.002)	(< 0.001)	(0.002)
Family relationship	−0.432***	−0.102	−1.114***	−0.596
	(0.002)	(0.419)	(0.003)	(0.184)
Friend relationship	−0.468***	−0.242**	−1.005***	−0.704**
	(< 0.001)	(0.013)	(< 0.001)	(0.023)
Business relationship	0.112	−0.023	0.316	−0.191
	(0.197)	(0.790)	(0.179)	(0.530)
No social relationship	−0.529**	−0.155	−1.210**	−0.699
	(0.013)	(0.419)	(0.040)	(0.333)
log(1+geographic distance)	−0.023*	−0.022*	−0.056	−0.072
	(0.095)	(0.098)	(0.111)	(0.133)
Tipper job: Buy side: analyst		1.181***		3.933***
		(< 0.001)		(< 0.001)
Tipper job: Buy side: manager		1.123***		3.728***
		(< 0.001)		(< 0.001)
Tipper job: Low-level employee		0.381**		1.510**
		(0.012)		(0.045)
Tipper job: Corporate manager		0.217**		1.638***
		(0.041)		(0.003)
Tipper job: Sell side		0.352***		1.647***
		(0.003)		(0.002)

	OLS		Ordered logit	
	Dependent Variable: Position in Tip Chain			
	(1)	(2)	(3)	(4)
Tipper job: Small business owner		1.112***		4.242***
		(< 0.001)		(< 0.001)
Tipper job: Specialized		0.666***		3.133***
		(< 0.001)		(< 0.001)
Tipper job: Unknown occupation		0.457***		2.432***
		(< 0.001)		(< 0.001)
Tippee job: Buy side: analyst		0.326**		0.884
		(0.041)		(0.209)
Tippee job: Buy side: manager		0.159		0.674
		(0.311)		(0.358)
Tippee job: Low-level employee		0.009		0.429
		(0.952)		(0.546)
Tippee job: Corporate manager		−0.119		−0.269
		(0.450)		(0.737)
Tippee job: Sell side		0.364**		0.969
		(0.048)		(0.212)
Tippee job: Small business owner		0.254*		1.187*
		(0.069)		(0.079)
Tippee job: Specialized		−0.279**		−0.861
		(0.029)		(0.240)
Tippee job: Unknown occupation		0.029		0.188
		(0.885)		(0.827)
Adjusted R^2	0.152	0.382		
Pseudo R^2			0.079	0.240
Observations	494	494	494	494

Table VII
Tippers and Tippees Social Relationships
This table reports the frequency of different types of social relationships among the 445 pairs of people in the insider trading data. When one person tips insider information to another person, they are 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.

Type of relationship	Count	Fraction of All Pairs	Fraction of Relationship Type
Family			
Dating/Engaged	7	1.6	6.7
Married	15	3.4	14.4
Parent-child	20	4.5	19.2
Siblings	25	5.6	24.0
In-laws	12	2.7	11.5
Other	9	2.0	8.7
Unspecified	16	3.6	15.4
All Family Relationships	104	23.4	
Business			
Business associates	85	20.8	54.5
Boss	38	9.3	24.4
Client	33	8.1	21.2
All Business Relationships	156	38.1	
Friends			
Acquaintances	3	0.7	1.9
Friends	109	26.7	69.9
Close Friends	44	10.8	28.2
All Friendship Relationships	156	38.1	
No social relation listed	98	24.0	

Table VIII
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.

				Percentiles				
	Mean	S.D.	Min	25th	50th	75th	Max	Observations
All	581.1	1,190.8	0	0.0	26.2	739.3	8,065.9	229
Family	466.3	1,080.1	0	0.0	14.3	322.5	5,350.4	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	1,986.5	13
Siblings	783.3	1,490.8	0	6.2	28.0	1,063.6	5,350.4	14
In-laws	1,110.5	1,751.5	0	9.6	216.5	1,626.3	5,350.4	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	4,452.0	98
Associates	334.5	751.6	0	0.0	16.8	236.8	4,452.0	57
Boss	198.4	395.1	0	3.9	24.8	53.4	1,235.4	22
Client	455.9	857.2	0	10.7	19.0	625.6	2,666.9	19
Friendship	715.1	1,352.4	0	4.0	28.4	1,045.8	8,065.9	106
Friends	708.2	1,247.7	0	4.5	32.1	1,077.6	6,622.1	72
Close friends	694.6	1,581.8	0	0.0	26.2	835.3	8,065.9	32
No social relation listed	962.2	1,680.0	0	15.0	80.9	1,117.4	5,358.7	14

Table IX
Original Source in M&A and Earnings Leaks
This table presents the frequency of different original sources of inside information in M&As and earnings announcements. For information leaks related to M&As, internal sources are those that are employed by the acquirer, target, or other firms, or are unknown. Other firms include potential and failed bidders. External sources include people that are employed by firms other than the merging firms. Consulting firms include human relations firms, investor relations firms, medical consultants, credit rating agencies, etc. For information leaks related to earnings, internal sources are people that are employed by the firm releasing the earnings statements.

	M&A				Earnings
	Acquirer	Target	Other/ Unknown	Total	
Internal sources					
Director	0	19	1	20	4
Officer	22	31	7	60	36
Employee	21	15	1	37	44
Total internal	43	65	9	117	84
External sources					
Accounting firm	15	6	0	21	20
Consulting firm (HR, IR, etc.)	4	3	0	7	13
Investment bank	13	10	14	37	0
Law firm	11	20	35	66	0
Stock market employee	0	0	0	0	5
Stolen	11	14	5	30	0
Other	2	1	0	3	1
Total external sources	56	54	54	164	39
Unknown sources	0	0	4	4	3
Total	99	119	67	285	126

Table X
Tipper and Tippee Occupations by Order in Tip Chain
This table presents the distribution of occupations for each link in a tip chain. The position in a tip chain is the distance from the original source of the inside information, where distance is measured as information links between people. "1" indicates the first link in the chain from an original source to all the people to whom the source shared the information. "2" indicates the links from the first people to receive the tip from the original source to all of the people with whom they share the information. "3" and "≥ 4" are defined analagously. Entries in the table present the fraction of all people at a given position in the tip chain that are employed in each of the listed occupations. Thus, columns sum to 100%. "Number" indicates the number of relationships for each position in the tip chain.

	Position in Tip Chain			
	1	2	3	≥ 4
Tippee Occupation				
Top executive	9.2	2.4	2.3	0.0
Corporate manager	5.5	2.1	0.8	0.0
Lower-level employee	9.6	12.8	9.9	0.0
Sell side/lawyer/accountants	10.8	14.1	13.7	7.3
Buy side: manager	12.5	22.1	16.0	25.5
Buy side: analyst/trader	19.3	14.5	28.2	34.5
Small business owner	10.4	10.7	10.7	3.6
Specialized occupation	10.4	4.8	3.1	0.0
Unknown	12.3	16.6	15.3	29.1
Number	415	290	131	55
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
Number	415	290	131	55

Table XI
Tipper and Tippee Characteristics by Order in Tip Chain
This table presents the characteristics of tippers and tippes for each link in a tip chain. The position in a tip chain is the distance from the original source of the inside information, where distance is measured as information links between people. "1" indicates the first link in the chain from an original source to all the people to whom the source shared the information. "2" indicates the links from the first people to receive the tip from the original source to all of the people with whom they share the information. "3" and "≥ 4" are defined analagously. "Degree centrality" is the number of connections of the person in a connected component.

	Order in Tip Chain			
	1	2	3	≥ 4
Characteristics				
Tippee female	8.1	5.1	17.3	2.5
Tipper female	11.7	13.4	4.7	11.3
Tippee age	41.8	40.8	38.1	37.5
Tipper age	42.5	41.0	35.4	33.7
Social Connections				
Family connection	25.1	16.2	29.0	12.7
Friendship connection	42.2	35.9	35.1	20.0
Business connection	28.9	47.9	34.4	63.6
No connection	20.5	18.3	16.8	12.7
Geographic distance - mean (miles)	505.0	731.2	459.8	217.4
Geographic distance - median (miles)	15.7	40.2	46.9	0.0
Trading				
Amount invested - average ($1,000s)	4,853.0	2,639.6	1,618.6	1,726.1
Amount invested - median ($1,000s)	200.4	250.1	280.1	492.7
Gross profit - average ($1,000s)	795.9	1,028.9	230.7	1,538.1
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
Insider volume/total volume (%)	2.8	4.7	2.9	5.4
Timing				
Time lapse from information to tip (days)	12.1	9.2	5.0	0.4
Tipped 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
Network Position				
Tippee degree centrality	2.9	2.3	2.0	1.8
Tipper degree centrality	1.8	4.3	5.0	4.6

Table XIII
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.

	Size of Component			
	1	2	3-5	≥ 6
Component Characteristics				
Density		1.0	0.6	0.2
Diameter		1.0	2.3	4.4
Average cluster		2.0	0.2	0.1
Personal Characteristics				
Female - tipper (%)	3.4	23.3	11.7	6.8
Female - tippee (%)		8.6	10.6	8.1
Age - tipper	47.8	43.8	43.2	41.5
Age - tippee		43.4	44.7	40.9
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
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
Timing				
Time lapse from information to tip (days)		11.3	15.4	9.3

Internet Appendix for

“Information Networks: Evidence from Illegal Insider Trading Tips”

Internet Appendix Table 1
Event Types
This table provides a breakdown of the types of corporate events in the sample. The data include 465 corporate events over the years 1996 to 2013 from SEC and DOJ case documents.

Clinical Trial/Drug Regulation	37
Clinical trial results	7
Regulatory approvals and rejections	30
Earnings	123
Earnings announcements	112
Earnings guidance	7
Earnings restatements	4
M&A	239
Acquisition announcement (trading in target stock)	216
Acquisition announcement (trading in acquirer stock)	3
Merger negotiation developments	3
Failed acquisitions	4
Joint ventures	3
Licensing	2
Restructuring	3
Target seeking buyer	1
Share repurchase	1
Strategic alliances/investments	3
Operations	13
Appointment/resignation of CEO	2
Business agreement/contract	9
Layoff	1
Other operations	1
Sale of Securities	35
Other	18
Analyst report	1
Dividend increase	1
Financial distress	2
Fund liquidation	1
Addition to stock index	1
Unspecified	12
Total	465

Internet Appendix Table 2
Job Titles of Insiders
This table provides a breakdown of the job titles in the sample. The data include 611 people involved in insider trading over the years 1996 to 2013 from SEC and DOJ case documents.

Top executive	107
Chairman	11
Board member	13
CEO	12
CFO	7
Officer	64
Mid-level corporate manager	51
Lower-level employee	59
Unspecified	40
Secretary	8
IT	11
Sell side: lawyer, accountant, investment banker	59
Investment banker	4
Sell-side analyst	3
Attorney	24
Accountant	13
Principal	15
Buy side: manager	60
Hedge fund manager	30
Portfolio manager	27
Investor	2
Venture capitalist	1
Buy side: analyst, trader	65
Trader	43
Buy-side analyst	22
Small business owner	39
Small business owner	35
Real estate broker	4
Specialized occupation	38
Consultant	16
Doctor	13
Engineer	9
Unknown	133
Total	611

Internet Appendix Table 3
Original Source in Other Events

This table presents the frequency of different original sources of inside information in information events other than M&As and earnings announcements. These events include announcements about clinical trial results, operations, sale of securities, and others. "Tip Firm"' refers to the firm for which the information is relevant. Internal sources are those that are employed by the tip firm. External sources include people that are employed by firms other than the merging firms. Service providers include human relations firms, investor relations firms, medical consultants, law firms, credit rating agencies, and others.

	Tip Firm	Failed/ Potential bidder	Regulatory Agency	Other/ Unknown	Total
Internal sources					
Director	2	0	0	0	2
Officer	9	0	0	0	9
Employee	12	0	0	3	15
Total internal sources	23	0	0	3	26
External sources					
Potential investor	0	34	0	0	34
Regulatory agency	0	0	27	0	27
Service providers	10	0	4	2	16
Total external sources	10	34	31	2	77
Unknown	0	0	0	3	3
Total	33	34	31	8	106

Internet Appendix Table 4
Tipper and Tippee Occupations by Order in Tip Chain: Long Versus Short Chains

This table presents the distribution of occupations for each link in a tip chain. The position in a tip chain is the distance from the original source of the inside information, where distance is measured as information links between people. "1" indicates the first link in the chain from an original source to all the people to whom the source shared the information. "2" indicates the links from the first people to receive the tip from the original source to all of the people with whom they share the information. "3" and "≥ 4" are defined analagously. Entries in the table present the fraction of all people at a given position in the tip chain that are employed in each of the listed occupations. Thus, columns sum to 100%. "Number" indicates the number of relationships for each position in the tip chain. "Short Tip Chains" have four or fewer members, thus, they have a maximum of three links in the tip chain. "Long Tip Chains" have more than four members.

	Short Tip Chains			Long Tip Chains			
Position in Tip Chain	1	2	3	1	2	3	≥ 4
Tippee Occupation							
Top executive	10.0	4.6	14.3	6.4	0.6	0.9	0.0
Corporate manager	4.4	1.5	0.0	9.6	2.5	0.9	0.0
Lower-level employee	11.2	14.5	0.0	4.3	11.3	11.1	0.0
Sell side/lawyer/accountants	11.5	16.0	28.6	8.5	12.6	12.0	7.3
Buy side: manager	12.5	22.9	21.4	12.8	21.4	15.4	25.5
Buy side: analyst/trader	16.5	13.0	14.3	28.7	15.7	29.9	34.5
Small business owner	10.9	9.2	0.0	8.5	11.9	12.0	3.6
Specialized occupation	10.9	2.3	0.0	8.5	6.9	3.4	0.0
Unknown	12.1	16.0	21.4	12.8	17.0	14.5	29.1
Number	321	131	14	94	159	117	55
Tipper Occupation							
Top executive	34.3	4.6	7.1	33.0	8.2	0.0	0.0
Corporate manager	12.5	9.2	0.0	18.1	8.2	3.4	0.0
Lower-level employee	16.5	6.1	14.3	14.9	4.4	11.1	3.6
Sell side/lawyer/accountants	25.5	6.9	42.9	28.7	6.9	28.2	7.3
Buy side: manager	0.3	8.4	14.3	3.2	20.8	17.9	12.7
Buy side: analyst/trader	2.5	22.1	0.0	0.0	32.7	30.8	70.9
Small business owner	0.9	4.6	7.1	0.0	8.8	7.7	1.8
Specialized occupation	1.9	20.6	14.3	0.0	7.5	0.0	0.0
Unknown	5.6	17.6	0.0	2.1	2.5	0.9	3.6
Number	321	131	14	94	159	117	55