Insider Trading and Networked Directors

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Keywords: Insider Trading, Director Networks, Network Analysis, Centrality, Opportunistic Trading, Routine Trading

JEL Classifications: G14, G34, G39

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Insider Trading and Networked Directors

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Abstract

We analyze the relation between insider trading and the networks of executive and non-executive directors in UK listed companies. While most existing studies focus on firm-specific private information, we find that non-firm-specific information – such as information on other companies and information on industry and market trends – plays an important role in insider trading behavior and performance. Well-connected directors trade shares less frequently and for smaller values. However, their transactions are more profitable, especially when they make consecutive opportunistic purchases in multiple companies on whose boards they sit. Taken together, well-connected directors are likely to outperform their peers with inferior networks.

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Insider Trading and Networked Directors

1. Introduction

As directors with access to private, price-sensitive information have an advantage over other investors when trading their shares (e.g., Jaffe, 1974; Elliott, Morse and Richardson 1984), the exploitation of this type of insider information for personal benefit is deemed to be unfair and hence illegal in most countries (Meulbroek, 1992; Fernandes and Ferreira, 2009). Even if insiders (whom we define as executive and non-executive members of the board of directors as well as former directors and incoming directors) trade during periods after the release of price-sensitive information on e.g., earnings and dividends, their trades may still contain information about the firm's prospects (Seyhun, 1986). One aspect of insider trades that has been largely ignored in the academic literature is that these trades may also reflect non-firm-specific information. Such information would be e.g., information on peer companies and competitors, and information on industry trends that insiders may hold given their direct or indirect connections to other corporate boards. This information is likely to generate gains for those trading on it.

To capture insiders' access to non-firm-specific information, we apply graph theory and network analysis to map corporate connections of executive and non-executive directors. By means of network centrality measures, we examine the relation between director networks and insider trading in the UK. We analyze the share transactions[1] carried out by the CEO, chairman, the other executive and non-executive directors, the former directors and the incoming ones.[2] We focus on how director centrality within director networks affects the following two fundamental aspects of insider trading: (1) the market reaction around the insider trading announcement day; and (2) the frequency, value, and profitability of insider trading. We distinguish between insider transactions of the following types: purchases and sales, transactions partitioned by the insider's position (e.g., CEO, or chairman), as well as routine versus non-routine or opportunistic trades. Since this study focuses on the information content of insider trading, we are particularly interested in non-routine trades (Cohen, Malloy and Pomorski, 2012).

We find that directors with superior networks and superior positions within their networks are deemed to hold more information because their share purchases trigger significantly higher

[1] Our insider transaction data also includes the exercise of stock options, which is examined separately in a subsample analysis.

[2] Former directors are the ones who served on the board for part of the past financial year. Incoming directors are those who have been appointed to the board or company, but have not yet started their appointment.

abnormal returns. This implies that director networks yield an informational advantage and increase the market reaction to director trading. Furthermore, this positive relationship between network characteristics and the market reaction is only observed for opportunistic purchase transactions. Our results are proven to be robust via a number of further analyses that include alternative network measures (normalized degree and betweenness as alternatives to normalized eigenvector centrality) and alternative insider trading measures (transaction sequences, clustered transactions, alternative event windows). They are also robust to further analyses that are based on a variety of subsamples (option-related transactions, unique daily transactions), analyses that control for important corporate events (e.g., transactions close to M&A announcements), and those that address endogeneity concerns. Moreover, when directors, who sit as executives or non-executives on the boards of multiple companies, carry out a sequence of trades in the shares of these companies, the market reacts stronger to the later transactions than to the initial transaction. Surprisingly, well-connected directors trade less frequently and for smaller total values annually. However, these directors can make higher trading profits (mainly by purchasing shares opportunistically rather than routinely) than the less-connected directors.

This paper makes the following four major contributions to the literature. First, the paper systematically examines the relation between insider trading and director networks captured by graph-theoretical measures. Our study is related to recent literature on sophisticated investors: Akbas, Meschke and Wintoki (2016) report that sophisticated institutions achieve higher returns when they trade shares of companies with large director networks, and Ahern (2017) finds that investors with access to valuable insider tips from executives via strong social connections earn abnormal returns. Second, our results imply that the gains from insider trading are not only determined by access to firm-specific information as documented by the existing literature, but also by access to information that is not firm-specific, such as information on peer companies and the broader industry. Networks enable directors to collect that type of information, and ultimately improve their insider trading performance. Third, while most studies on insider trading focus on trading performance, we also investigate the trading patterns (trading frequency, sequenced transactions, clustered transactions, and the direction of sequenced transactions). We find that better-connected insiders, whose transactions induce strong positive market reactions at the announcement, are not necessarily the most active ones. As they have an informational advantage, they purchase more selectively, i.e., less frequently and for lower share values than the less well-connected directors. Finally, our analysis uses the partitioning of insider transactions into opportunistic and routine trades as proposed by Cohen et al. (2012). More specifically, opportunistic purchases by well-connected directors do not only trigger the largest market reactions, but they are also the most profitable ones. We extend Cohen et al.'s (2012) partitioning by distinguishing transaction sequences from single transactions. As stated above, we find that the timing of a trade within a sequence of trades matters.

2. Literature and conjectures

2.1 The information content of insider trades

That insider purchases (sales) trigger positive (negative) abnormal stock returns at announcement and even over longer time intervals has been extensively documented by a number of studies.[3] The reason why the disclosure of an insider trade causes the market to react is that an insider purchasing or selling shares or exercising options (followed by either share retention or selling) is costly to the insider if he gets it wrong and is therefore a credible signal to the market.

Some early studies, such as Lorie and Niederhoffer (1968) and Jaffe (1974), show that insiders trade on privileged information, which moves the share price more than when other market participants trade. Insiders are believed by market participants to possess superior information about future earnings and cash flow realizations, as shown by Ke, Huddart and Petroni (2003) and Piotroski and Roulstone (2005). Insiders also trade more effectively by timing their trades: Their sales often occur after the share price has increased (by on average 3% over the preceding month) and purchases occur after the share price has decreased (by -1.27% over the preceding month) (Fidrmuc et al., 2006). The above studies and Berkman, Koch and Westerholm (2017) agree on the differential informativeness of insider purchases and sales, with insider purchases triggering stronger price reactions – in absolute value – than insider sales. Indeed, sales may not only be driven by information on the company's future profitability, but also by insiders' needs for liquidity and diversification of their personal wealth, reasons which are not informative to the market. Consequently, insider sales have weaker information value than purchases (Lakonishok and Lee, 2001; Friederich et al., 2002; Cohen et al., 2012).

Specific types of insiders, such as the CEO and the executive chairman, may be better informed about the firm as they are involved in the operational side of the business, including capital budgeting and forecasting future cash flows. Hence, it is likely that the market gives more weight to transactions by such insiders. This argument underlies Seyhun's (1986) information hierarchy hypothesis, whereby the trades of the CEO and the executive chairman generate stronger abnormal returns than those by the other executive directors. In turn, the trades of the latter generate stronger abnormal returns than those by the non-executive directors. Seyhun (1986) and Tavakoli, McMillan and McKnight (2012) observe market reactions congruent with the information hierarchy, but most other studies fail to find supporting evidence. For example, Jeng, Metrick and Zeckhauser (1999) demonstrate that trading by senior managers (e.g., the CEO) triggers smaller rather than larger market reactions. The reason they provide is

3 See, for example, Rozeff and Zaman (1988), Lin and Howe (1990), Hillier and Marshall (2002), Friederich, Gregory, Matatko and Tonks (2002), Del Brio (2002), Ke, Huddart and Petroni (2003), Fidrmuc et al. (2006), Marin and Olivier (2008), Ravina and Sapienza (2010), Tavakoli, McMillan and McKnight (2012), Cohen et al. (2012), Rogers, Skinner, Zechman (2016), and He and Rui (2016).

that the CEO's trading is likely more closely scrutinized by the regulator and the market, which induces the CEO to trade more cautiously. Furthermore, Fidrmuc et al. (2006) report that the strength of the market reaction to insider trading is affected by the ownership and control structure of the firm: For firms with large equity blocks held by corporations or by individuals and families not related to the directors, the market reaction is smaller than for firms with widely-held ownership or large equity blocks held by institutional investors. The authors argue that corporations and families are more likely to be active shareholders who monitor their investee firms, in contrast to institutional shareholders, which in the UK generally tend to be passive. As the presence of active owners reduces the information asymmetry between the management and the market, the informational content of insider trades is also reduced. In contrast, the market reaction is stronger in the presence of large institutional investors. Similarly, Ravina and Sapienza (2010) find that insider trades are more informative for firms with weaker corporate governance.

Furthermore, smaller companies disclose less information, which makes information asymmetry more severe and hence enhances the informational content of insider transactions (Lakonishok and Lee, 2001; Tavakoli et al. 2012). Insider trading has also been studied around major corporate events. For example, Agrawal and Nasser (2012) report that, prior to a takeover bid, insiders in the target firm may have private information on the negotiations and therefore reduce their (routine) sales to effectively achieve an increase in net purchases.

In sum, insider trades convey informational value, which depends on the traits of the insider (e.g., their position within the firm) and on firm characteristics (e.g., size, ownership and control structure, degree of informational transparency, and governance characteristics). Since information plays a key role in insider trading, we now turn to the information gathering potential of director networks, which may affect a director's access to information as well as the dissemination of information.

2.2 Director networks and the dissemination of information

Information dissemination across networks was first studied in sociology by means of graph theory. Early studies in economics investigate the role of networks in individuals' search for jobs (e.g., Granovetter, 1977). Recent studies in finance (e.g., Renneboog and Zhao, 2014) suggest that networks are instrumental for corporate decision making as they provide access to important information. Such information is generated by an individual (or firm) in the network and it then spreads across the individual's (or firm's) connections. Other individuals (firms) with connections to the information source are also able to take advantage of the information. Individuals who are more "central" in the network are on average more likely to have better access to information. Further, individuals with connections to other well-connected individuals will have markedly better access to information than more isolated individuals.

More specifically, the benefits of networks in terms of their information value have been highlighted for corporate decision-making. For example, Davis, Yoo and Baker (2003) describe the information flow across boards of directors as a point-to-point contagion process, whereby directors share the information obtained via their other board seats. By means of a case study of the Cambridge hi-tech cluster, Myint, Vyakarnam and New (2005) demonstrate that multiple directorships are valuable as they create new business opportunities and transfer management expertise across firms. More recently, Rossi, Blake, Timmermann and Tonks (2016) show that well-connected investment managers exploit investment opportunities through their connections, thereby achieving superior portfolio performance. Several other large-scale studies provide evidence of better corporate decision-making via information obtained through director networks, which ultimately improves corporate performance. For example, Cai and Sevilir (2010) and Renneboog and Zhao (2014) show that director networks increase the efficiency of M&A transactions, in that board connections between the bidder and the target reduce asymmetric information about the target. This results in a shorter negotiation time, a larger proportion of cash used as a means of payment, and a greater probability of successfully completing the negotiation. More generally, Geletkanycz and Boyd (2011) find that the CEO's non-executive directorships are positively related to the long-term performance of his firm when it faces competitive challenges. Finally, Omer, Shelly and Tice (2014) report that non-executive directors' networks provide information on market trends, business innovations, and effective corporate practices.

Networks matter not only for the corporate decision-making, but also for individual careers. Connections affect managerial compensation, top management succession and turnover, and the selection of non-executive directors. For instance, Renneboog and Zhao (2011) and Horton, Millo and Serafeim (2012) demonstrate that a CEO's direct connections and indirect connectedness affect his power and information-collection ability, both of which translate into higher CEO remuneration. Fich and Shivdasani (2006) and Guedj and Barnea (2009) report that CEO turnover-performance sensitivity is significantly lower for firms with highly connected boards. Moreover, better-connected CEOs have an advantage in the managerial labor market. For example, Kirchmaier and Stathopoulos (2008) find that growth companies prefer to recruit CEOs with larger social networks. Finally, Liu (2014) observes that better-connected CEOs are more likely to find a new CEO position in another firm[4].

A recurring pattern in the above literature is that networks affect the information-collection ability of directors: Directors with better networks have better access to non-firm-specific

[4] Another potential effect of networks is managerial power. In the context of insider trading, Bourveau, Coulomb, and Sangnier (2016) analyse the 2007 French presidential election and find that politically connected directors are less likely to comply with trading disclosure requirements, trade closer to major corporate events, and their transactions trigger larger abnormal returns.

information, and may therefore be better able to identify more profitable trading opportunities. Therefore, we conjecture that:

The market reaction to the announcement of the insider transaction of a well-connected director is stronger (Conjecture 1).

We are particularly interested in the trading behavior of directors sitting on multiple boards. When these directors trade in multiple companies within a short period of time (i.e., 30 days), investors may notice the connections between these transactions and respond more strongly to the later trades. We therefore conjecture that:

After an initial insider transaction, the market reaction to subsequent transactions in connected companies by the same insider becomes stronger (Conjecture 2).

We expect that well-connected directors are more likely to hold valuable price-sensitive information, and therefore have more trading opportunities:

Well-connected directors trade more frequently and their annual combined transaction value is higher (Conjecture 3).

Conversely, well-connected directors may be more selective in their trades and better able to identify profitable trading opportunities given their superior information:

Better-connected directors trade less frequently and for smaller transaction values, but their better access to information makes it easier for them to select profitable trading opportunities such that they generate higher insider trading profits than less-connected directors (Conjecture 4).

3. Methodology

3.1 Networks

We apply graph theory to our network analysis in order to capture the informational advantage of directors. We present an illustrative example in Figure 1, which includes six companies (circles 1-6) and 24 directors (letters A-U). Directors A, C, F and S sit on the boards of two companies each. All remaining directors sit on just one board.

[Insert Figure 1 about here]

In graph theory, a vertex is the fundamental unit of which graphs are formed, which represents, in this context, a single (executive or non-executive) director. Two directors sitting on the same board are defined as adjacent vertices and are hence directly connected directors (e.g., A and B). Directors with a greater number of direct connections – which we measure by *Degree*, the most commonly used centrality measure – may have more advantageous positions within the overall network and therefore have better access to information. However, degree does not always accurately reflect the positional advantage of a vertex in the network, because vertices at very different positions may still have the same degree score. For example, directors

R and U in companies 4 and 5 both have two colleagues, i.e., two direct connections and a degree equal to two, but director R is more likely to have better access to information than director U, thanks to his colleague F's position in large company 3, which is in turn connected to companies 1 and 2. A similar conclusion applies to directors B and M who are both directly connected to seven colleagues and are arguably better positioned than directors R and U in terms of their access to information within the whole network. The fact that director B is connected to colleagues A and F in companies 1 and 4 gives B an advantage over M (who is connected to only one company, company 3, via her colleague C).

In the context of insider trading, price-sensitive news about company 4 is likely to be known to director B before it reaches director M. Therefore, the degree, i.e., the number of direct connections, may not truly reflect the informational advantage associated with a specific network position. In other words, it is important to consider not only the number of connections but also their importance, i.e., their positions relative to other important vertices. For this reason, we also use the concept of indirect connections; e.g., P and B are indirectly connected via A. The sum of the connections or links between two indirectly connected vertices is a path (e.g., the path between Q and K contains three connections: Q-F, F-C and C-K). Although multiple paths between two vertices may exist, the geodesic path is the one with the smallest number of connections between two given vertices (the shortest path). *Closeness* of a vertex is based on these indirect connections and defined as the inverse of the sum of all geodesic paths (d_G) from vertex v to any other vertex t:

$$C_c(v) = \frac{1}{\sum d_G(v,t)}$$

The *betweenness* of vertex v is the sum of its betweenness ratios, which are defined as the number of geodesic paths from vertex s to vertex t passing through vertex v, divided by the number of geodesic paths from s to t. In formulaic form, this is:

$$C_B(v) = \sum_{\substack{s \neq v \neq t \in V \\ s \neq t}} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

where the denominator is the number of geodesic paths from vertex s to vertex t, and the numerator is the number of geodesic paths from s to t with vertex v on the geodesic path.

Eigenvector centrality of vertex v ($C_E(v)$) is equal to the sum of all adjacent vertices' eigenvector centrality scores:

$$C_E(v) = \frac{1}{\lambda} \sum_{j=1}^{N} A_{v,j} C_E(j)$$

The advantage of eigenvector centrality over the other centrality measures is that it not only captures how many vertices are linked to the target vertex (degree), but also considers the importance within the network of those linked vertices (the degree of each of the linked vertices). Consequently, a vertex has a higher eigenvector centrality score if it is connected to more vertices with higher scores. The calculation process begins with assigning a score of one to all the vertices and, in each iteration, the score of vertex v is calculated as the sum of all adjacent vertices' scores received in the previous iteration. In the above formula, matrix A is an adjacent matrix capturing whether any vertex j is adjacent to the target vertex v. As the centrality score for each vertex evolves after every iteration, the factor λ ensures that the centrality scores converge after several iterations. We shall use eigenvector centrality in our baseline models and use the other centrality measures in robustness checks. Given that network sizes vary over time, we normalize the centrality measures by the size of the entire network in each year. In the regression analysis below, we use these normalized centrality measures. The results are not qualitatively different if we use the non-normalized centrality measures.

3.2 Empirical approach

3.2.1 Multilevel mixed-effects linear regression at the transaction level (testing conjecture 1)

Since a director's transactions may be influenced by specific traits or habits and by corporate specificities, repeat transactions may not be independent. Given that we face a hierarchy of levels with transactions (dimension k) by individual directors (dimension j) in a given firm (dimension i), we estimate multilevel mixed-effects models to capture director-specific and company-specific effects as well as various other factors influencing insider trading. To test the validity of our first conjecture on the market reaction to trades, we include as independent variables the director's network centrality measure (normalized eigenvector centrality in the base models), transaction characteristics, director traits, and company characteristics. In a nutshell, we estimate the following model for the k^{th} transaction of the j^{th} director in the i^{th} company:

$$Market\ reaction_{ijk} = \beta_0 + \beta_1{*}Trade\_characteristics_{ijk} + \beta_2{*}Director\_centrality_{ij} + \beta_3{*}Director\_characteristics_{ij} + \beta_4{*}Firm\_characteristics_j + u_i + u_j + \varepsilon_{ijk} \tag{1}$$

where u_i stands for director-specific fixed effects, u_j for company-specific fixed effects, and ε_{ijk} is the error term.

3.2.2 Identification of sequenced transactions (testing conjecture 2)

We examine whether directors who sit on multiple boards trade shares in more than one of their companies. If a director trades shares within a period of 30 days in two or more of his companies, we consider these transactions to be *sequenced transactions*. Such transactions make up 3.5% of all transactions. Sequenced transactions may contain more information and therefore eventually trigger stronger market reactions. Sequenced transactions by the same director form a *sequence*. We have identified 462 sequences of transactions.

Sequence numbers 140 and 141 are shown as illustrative examples in Table 1 and capture the transactions conducted by director G in companies A, F and S, on whose boards director G sits. Transactions 1 to 4 occurred in early 2013 and form sequence 140; some other transactions (5 to 9) take place more than 30 days after the *final* transaction of the previous sequence and are therefore treated as a new sequence (number 141).[5] The variable *Purchase* equals one if the transaction is a purchase transaction, and zero otherwise. We assign *ranks* to each transaction based on its order within the sequence. When two transactions take place on the same day, they are assigned the same rank. In order to label a transaction as a 'same' or 'reverse' transaction, we first calculate the average direction of the previous transactions within the sequence over the past 30 days allotting a one to a purchase and a zero to a sale, unless the purchase or sale is on the first day of the sequence. For example, for transaction 4 on May 24, 2013, three transactions (1, 2 and 3) took place within the previous 30 days, two purchases and one sale. Therefore, the average past transaction direction is 2/3 = 0.666. We subsequently calculate the difference between the direction of transaction 4 on May 24, 2013 (one as it is a purchase) and the average past transaction direction (0.666). We conclude that transaction 4 is 0.333 different from the average past transactions in terms of its direction. If the difference is smaller than 0.5, we consider that this transaction is in the same direction as past transactions (*sequenced-same*). If it is larger than 0.5, the transaction is in the opposite direction to past transactions (*sequenced-opposite*). If the gap is precisely 0.5, we consider it is a mixed case (*sequenced-mixed*).

[Insert Table 1 about here]

3.2.3. Random-effects Poisson regressions and random-effects Tobit regressions at the director level (testing conjectures 3 and 4)

In order to examine trading activity (frequency and value), we aggregate all transactions for a director according to type (purchase and sale) by year. In the analysis of trading frequency, the dependent variable is the number of purchase or sale transactions conducted by the director in a given year. Since the dependent variable is a count variable, we estimate Poisson regressions. Furthermore, as directors may be influenced by company-specific effects, we use the following random-effects Poisson regression:[6]

$$\textit{Annual number of transactions (purchases or sales)}_{ij} = \alpha + \beta_1 \textit{*Director\_centrality}_{ij} + \beta_2 \textit{*Director\_characteristics}_{ij} + \beta_3 \textit{*Firm\_characteristics}_{j} + u_j + \varepsilon_{ij} \quad (2)$$

[5] The reader should note that sequence 141 covers more than 30 days given that the last two transactions are made on January 21, 2014 whereas the first transaction dates back to December 2, 2013. However, the last two transactions are still within a 30-day period from the previous transaction, which was made on December 23, 2013. Hence, we consider these five transactions to be sequenced transactions.

[6] As some directors do not trade during the sample period, we also estimated zero-inflated Poisson regressions. The results obtained are similar to the results from the Poisson random effects models.

where u_j represents the company-specific fixed effects, and ε_{ijk} is the error term.

We also analyze what determines the value of the purchase or sale transactions. When a director does not trade in a given year, the annual value of his purchases and sales is set to zero; i.e., the dependent variable is left-censored at zero, which is why we estimate the following random-effects Tobit regression:

$$Annual\ value\ of\ transactions\ (purchases\ or\ sales)_{ij} = \alpha + \beta_1 * Director\_centrality_{ij} + \beta_2 * Director\_characteristics_{ij} + \beta_3 * Firm\_characteristics_j + u_j + \varepsilon_{ij} \quad (3)$$

where u_j captures the company-specific fixed effects, and ε_{ijk} is the error term. Note that, in Equations (2) and (3), the data is aggregated at the director-year level. Therefore, we do not control for transaction characteristics.

We examine the profitability of insider trading by measuring the total profit accumulated by the director over a given year. We perform (i) a transaction profit analysis for which we adopt a model similar to Equation (1) with profits earned (or losses avoided in the case of sales) as the dependent variable and (ii) a director annual profit analysis for which we calculate the total profit the director has earned from all his transactions during the calendar year. We relate these profits to director centrality, director characteristics, and the average firm characteristics of all the firms on whose board the director has sat. We estimate the above relationship by means of the following random-effects model:[7]

$$Annual\ profit\ of\ transactions\ (purchases\ or\ sales)_{it} = \alpha + \beta_1 * Director\_centrality_{it} + \beta_2 * Director\_characteristics_{it} + \beta_3 * Avg.\ Firm\_characteristics_{it} + \varepsilon_{it} \quad (4)$$

In all regressions, we include dummy variables for year and industry to control for potential time effects (e.g., the financial crisis) and industry-specificities (as in some industries, networks may be more prevalent).

4. Data

4.1 Insider trading characteristics

The insider trading data is obtained from *Directors Deals*,[8] a specialist data provider. The data includes all disclosed share transactions by executive and non-executive directors, former directors and incoming directors[9] in publicly listed UK companies (including FTSE AIM) over

[7] We do not estimate a company fixed-effects model given that some directors trade in the stock of more than one company.
[8] On October 31, 2016, Directors Deals Ltd. was acquired by Smart Insider Ltd.
[9] Directors Deals also includes transactions by PDMRs (people discharging managerial responsibilities), who are managers who do not sit on the board but have access to price sensitive information. However, as PDMRs are not included in the directorship data from BoardEX (which we used to construct director networks), we focus only on directors (including former and incoming ones).

the period 2004 to 2014. It is worth noting that insider trading regulation and practice in the UK market is different from that of the US. Overall, the UK insider trading law is less restrictive relative to the US regulation, as it is more difficult in the UK to identify guilty parties and to prosecute individuals[10]. Specifically, the US short swing rule that restricts officers and insiders from making short-term profits by purchasing and selling shares within a six-month period is absent in UK regulation. Such regulatory differences may explain the divergence in insider trading behavior (e.g., timing and value) and outcome (e.g., profits and market reaction) between UK and US. For example, Lakonishok and Lee (2001) find in the US abnormal returns only exist for purchases in small firms. However, Fidrmuc et al., (2006) report that insider transactions are generally informative in the UK.

For each transaction, we identify the insider, transaction date, announcement date,[11] transaction timing (in relation to other insider transactions and trading bans or close periods), number of shares traded, and type of transaction (purchases including the acquisition and retention of shares after the exercise of stock options (purchases post-exercise) or sales including the subcategory of sales immediately after the exercise of stock options (sales post-exercise)).

After removing companies from the financial services industry and observations with incomplete information, we obtain a sample of 25,644 transactions.[12] Descriptive statistics are shown in Table 2. Panel A distinguishes between purchase transactions (73.4%, including Purchases, Contract Buys,[13] and Exercises) and sale transactions (26.6%, including Sales, and Sales Post-Exercise). In our sample, the number of purchases exceeds that of sales, which is contrary to what US studies observe. Nevertheless, this pattern is in line with other UK studies. For example, Fidrmuc et al. (2006) report that the average number of purchases per firm-year (including option exercises) is about twice the number of sales (2.08 and 1.09, respectively). As

[10] See speech "Insider Dealing in the City" by Margaret Cole, Director of Enforcement, FSA 2007.

[11] According to the UK Financial Services Authority's (FSA – in 2013 replaced by the newly formed Financial Conduct Authority (FCA)) reporting requirements (DTR 3.1.2 through to DTR 3.1.8), PDMRs and their connected persons "must notify the issuer in writing of the occurrence of all transactions conducted on their own account in the shares of the issuer, or derivatives or any other financial instruments relating to those shares within four business days of the day on which the transaction occurred". Furthermore, "A director of a fully listed company is obliged to notify their company of any dealing in its shares within four business days, and the company must pass that information to the market by the end of the following business day." Our data show that 55% of directors disclose the trade on the trading day itself or the next day and that the reporting lag between the trade and its announcement amounts to 1.6 days, which remains stable across our sample period.

[12] We also studied the full sample, including companies in the financial services industry, and our results are upheld. Further, when comparing the companies from the financial services industry to the other companies, we find that the market reaction to insider trades for the former is lower in absolute value. However, we do not find any differences in terms of trading activity.

[13] Directors may buy shares on the market as part of a contractual agreement with the company, which may comprise a matching award through a regular share purchase plan. A typical example is that of a director deferring a proportion of his annual bonus and converting the deferred bonus into shares; the company then provides him with a matching number of shares. The latter shares may be subject to further performance criteria and are recorded as Contract Buys in our data.

directors may time the exercise of their options, purchases through option exercises may also contain information, which is the reason why we retain them in our sample (we will exclude them in a robustness analysis).

Some insider transactions may be driven by an informational advantage and hence act as a signal, whereas other insider transactions may be carried out for liquidity reasons or for other routine purposes (e.g., sales after the periodic exercise of stock options). We therefore adopt a method similar to Cohen et al. (2012) to partition insider trades into 'opportunistic' and 'routine' transactions. More specifically, if a director has conducted one transaction of the same type (purchase or sale) in the same month in each of three consecutive years in one company, we consider these three transactions as well as any subsequent transaction in that same month over the following years to be routine transactions.[14] We label all other transactions as opportunistic. It should be noted that a given insider may have engaged in both routine and opportunistic trades during the same year. Applying this definition, Panel A of Table 2 shows that 89.5% of all transactions in the sample are opportunistic transactions (66.2% of which are purchases and 23.3% are sales). Panel B focuses on the insider's position: executive directors (including the CEO) account for 47.9% of the purchases and 77.6% of sales. Non-executive chairmen also trade actively and their trades account for 16.5% and 7.4% of purchases and sales, respectively.

[Insert Table 2 about here]

While Table 2 highlights that insider purchases occur more frequently than sales, Panel A of Table 3 shows that sales are much larger than purchases with respect to all the measures (number of shares traded by transaction, transaction value in GBP, and transaction value as a percentage of the firm's market capitalization): The average sale amounts to GBP 702,027 whereas the average purchase only amounts to GBP 100,838. Further, the size of opportunistic purchases (sales) is also on average much larger than that of routine purchase (sale) transactions. In terms of GBP value (not tabulated), the average opportunistic purchase (sale) amounts to GBP 105,799 (GBP 727,371) compared to only GBP 55,174 (GBP 520,051) for routine purchases (sales). When we aggregate transactions on an annual basis, several patterns emerge: The annual total value of sales is more volatile than that of purchases (Figure 2). The annual sales value peaked in 2007, decreased substantially in 2008-2009, recovered steeply from 2010 onwards, and in 2013, the average total annual sales value almost reached its pre-recession level. In turn,

[14] The director-level approach in Cohen et al. (2012) identifies routine vs opportunistic traders according to their trading habits over a three-year period, and all these directors' trades over the subsequent years are then categorized as either routine or opportunistic. Alternatively, the trade-level approach defines routine trades as trades that are done every year at about the same time (month); e.g. if a director sells shares each year in December, then the December sales are considered routine; when he occasionally but not systematically purchases shares in e.g. June or September, then these trades are considered as opportunistic. The trade level approach thus allows a director to conduct both routine and opportunistic trades in a given year. We adopt the trade-level approach, which ends up with less routine transactions than we would find with the director-level approach.

the annual purchase value peaked in 2006, prior to the recession. This peak was to a great extent driven by option exercises (39.7% of purchases). Total purchase value then dropped and remained stable for the rest of the period. Since the 2008 financial crisis, the proportion of routine transactions had increased significantly up to 15% and did so until 2012. It then declined to 8%. Panel B of Table 3 reports the transactions by insider position: the chairman and CEO on average purchase the largest stakes, i.e., 0.175% (0.136%) of market capitalization, respectively. They also sell the largest stakes, i.e., 0.439% and 0.240%, respectively.

[Insert Table 3 and Figure 2 about here]

We also gather information on the timing of the transactions (not tabulated) and create the following variables:

Clustered transactions

If two insider transactions of the same type (purchases or sales) – note that they do not need to be carried out by the same insider – are made on the same day in a specific company, we classify them as *clustered* transactions. As many as 53.5% of the transactions are clustered. We expect stronger market reactions to clustered transactions if they are in the same direction (i.e., they are all purchases or all sales) as the signal may then be reinforced.

Sequenced transactions

Sequenced transactions (see also above) are conducted within a 30-day period by the same director in multiple companies on whose boards he sits. We expect that sequenced transactions of the same direction (i.e., they are all purchases or all sales) reinforce one another and are therefore followed by stronger market reactions.

Before and after close period

The UK Financial Conduct Authority (FCA) has issued regulations on insider trading, which limit the extent to which directors and other individuals can take advantage of insider information; e.g., directors are banned from trading in the shares of their company 60 days prior to the release of the preliminary, interim, and annual earnings announcement (see also Fidrmuc et al., 2006).[15] The period, during which insiders are not allowed to trade, is referred to as the 'close' period. We collect data on the timing of the insider trades relative to the close period. Insider transactions may have different information content, depending on whether they occur before or after the close period (Garfinkel, 1997; Hillier and Marshall, 2002). Therefore, we identify transactions one week (i.e., seven calendar days) before the commencement of the close period and one week after the end of the close period.[16] Whereas the number of insider transactions in the week *before* the close period is no different from the number of insider transactions across all other periods of the year, we do find significantly more transactions in

[15] If the company makes quarterly earnings announcements, the close period around these announcements is 30 days.

[16] When using a 15-calendar-day and a 21-calendar-day window, we find that the results are upheld.

the week *after* the close period.

4.2 Insider networks

The director networks are built by means of board data from BoardEx[17] and the network analysis software Gephi (Bastian, Heymann and Jacomy, 2009) and Ucinet (Borgatti, Everett and Freeman, 2002). We calculate the centrality measures (eigenvector centrality, degree, closeness, and betweenness) to measure the level of connectedness of each individual director based on their direct and indirect connections to all other directors in listed UK companies. It should be noted that this network analysis is only an approximation of the actual director-based network as we do not possess the same detailed information on non-listed firms. Still, a network analysis for a country such as the UK captures connections far better than for, e.g., Germany where relatively few firms are listed: Germany has only about 40% of the number of UK listed firms although its economy is about 1.4 times the size of the UK economy.

Our network analysis does not only capture the connections of the incumbent directors in a given year, but it also includes the connections of the former directors, i.e., the directors who left the company in the previous financial year. There are three reasons for their inclusion. First, former directors may still possess inside information. In support of this argument, Fidrmuc et al. (2006) find that the market still reacts to share trading by former directors when such trading is disclosed. Second, UK insider trading regulation is not restricted to current directors, but it applies to any individual with access to price sensitive information, which also includes former directors.[18] Third, it is reasonable to assume that directors who recently left the firm still have connections with their former colleagues and may still play a role in the networks by bridging information gaps and/or strengthening existing connections. Hence, for the sake of network completeness, we also examine the trading of former directors who recently (i.e., less than one year prior to their trading) left the firm.[19]

Our main centrality measures are reported in Table 4 where a larger value reflects a more central position within the network and better connectedness. The centrality measures are calculated based on the networks including all the directors. Descriptive statistics in Table 4 are based on the subsample of trading directors. On average, directors have 12.3 direct connections (with a median of 10) and the most extreme case is a busy director sitting on seven boards,

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[17] We do not use director information provided by Directors Deals as it only includes information on the directors who trade. As constructing networks based on this subsample would create a severe sample selection issue, we rely on BoardEx to construct the complete director network comprising all trading and non-trading directors.

[18] According to Part V – Insider Dealing of the Criminal Justice Act 1993, “An individual who has information as an insider is guilty of insider dealing if, […], he deals in securities that are price-affected securities in relation to the information.”

[19] As a robustness test, we exclude former directors and obtain very similar results.

yielding 56 direct connections.[20] For the reasons stated in Section 3.1, rather than using the raw centrality measures, we normalize the centrality measures by the size of the entire network in a given year.[21]

[Insert Table 4 about here]

4.3 Control variables

The control variables we will include in our models comprise director traits (age, gender and whether the director leaves the firm (close to retirement or not) in a specific year); firm characteristics (return on assets (ROA), leverage (total debt to assets ratio), default risk (interest coverage, i.e., EBIT/interest), tangibility (fixed assets over total assets), dividend payout (dividend over net income), size (logarithm of total assets);[22] board characteristics (ratio of non-executives on the board, female director ratio, CEO-chairman duality, ratio of independent directors on the board); and the ownership structure (see Appendix 1 for the detailed definitions of the measures used).[23] We report the descriptive statistics of control variables in Panel B of Table 4. The average age of the directors is about 54 years and 94.4% of the directors are male. We consider departures at the age of 65 and above to be natural departures, i.e., departures motivated by a desire to retire. According to this definition, about 15% of all directors leave the firm as a consequence of retirement. About 57.3% of the board members are non-executive directors, and in only about 4.8% of firms the CEO also chairs the board. The average (median) ROA of our sample firms amounts to 3.9% (6.1%) and leverage is 18.2% (15.0%). Interest coverage is on average about 15, fixed assets as a percentage of total assets amount to 25%. Institutional shareholders are the most important type of shareholder, holding on average 57% of the equity. Corporates and families/individuals hold average stakes of 9.8% and 7.8% of the equity, respectively.

5. Empirical analysis

5.1 Market reaction to insider trading

The cumulative abnormal stock returns (CARs) around the announcement day of an insider trade are reported in Panel A of Table 5. We use the period of day -200 to day -21 (relative to the event day, i.e., day 0) − as per Fidrmuc et al. (2006) – as the estimation window to obtain

[20] Appendix 2 shows the distribution of the number of board memberships seats held by the directors. Most directors hold only one directorship, about one quarter of the directors sit on at least two boards, and about 10% of the directors sit on three or more boards in any given year. Executive directors often hold fewer external board seats than non-executive directors.

[21] The betweenness scores often take on the value of zero since a lot of vertices never appear on the geodesic paths between other vertices, which explains the zero median.

[22] We do not include transparency (analyst following), and index membership (of the FTSE100 or overseas stock indices) in the regressions as these variables are strongly correlated with firm size.

[23] Descriptive statistics are not tabulated for reasons of parsimony; tables are available upon request.

the beta parameter for the market model, which is then used to calculate the CARs for different event windows, i.e., (-20;-1), (0;1), (0;5) and (0;10), where (0;1) refers to the announcement day and the following day. We confirm the results from previous studies: The market reacts positively to insider purchases and negatively to sales. All the CARs are significantly different from zero according to the t-statistics with robust standard errors (Del Brio and Lyon, 1997). Insider purchases are on average associated with a stronger market reaction in absolute value (1.4% over the announcement window (0;1) and 2.0% over a longer window (0;10)) than sales (-0.2% over (0;1) and -0.7% over (0;10)). This suggests that insider purchases constitute a stronger signal than insider sales that may frequently occur because of liquidity needs.

There is some evidence that directors time the market: They purchase after the share price has declined for a month (by on average 1.1% compared to the market) and sell after the price has increased (by 0.6%). We distinguish between routine and opportunistic trades and conclude that for the (0;1) window the market reacts significantly stronger to opportunistic purchases (1.5%) than to routine purchases (0.4%). For sales, the difference is smaller: Opportunistic sales trigger on average significantly negative CARs of -0.2% whereas the CARs of routine sales are not significantly different from zero.

[Insert Table 5 about here]

Panel B investigates whether the market reaction to the announcement (CAR (0;1)) depends on the position of the insider. Purchases by CEOs and chairmen trigger the strongest market reactions (1.7% and 2.1%, respectively) compared to other executive (1.2%) and non-executive directors (1.3%), and incoming (0.6%) and former directors (1.1%). There may be two reasons for the larger market reaction to trades by CEOs and chairmen. First, the two most senior board members may have access to better firm-specific information, which turns their trades into stronger signals. Second, as documented in Panel B of Table 2, the CEOs and chairmen also trade larger stakes, which are likely to be more visible. When it comes to sales, the market reaction to trades by executive and non-executive directors is mostly significant and negative, but much smaller (it is between 10 and 50 basis points in absolute value).

In Panel C, we present descriptive statistics for the market reaction (CAR (0;1)) to sequenced transactions, i.e., transactions conducted by the same director in multiple companies within a period of 30 days. As defined in Section 4.1, a sequenced transaction can be in the same, opposite, or mixed direction (see Section 3.2.2 for the definition).[24] For the purchase transactions, the market reacts strongly to sequenced-same purchase transactions (1.2%); the reactions to sequenced-mixed and sequenced-opposite transactions on the other hand are not statistically significant (as are the reactions to the sales), but the relevant subsamples are small.

[24] Since we need previous transactions to determine the direction of a transaction in a sequence, we cannot include first transactions in sequences in any of the three categories.

The market reactions to sequenced-same purchases are similar to the market reactions to the purchase transactions for the entire sample (1.4% in Panel A). Still, sequenced transactions involve less value than other transactions: For example, in the sequenced-same purchase subsample, the average market capitalization traded by the CEO and chairman is 0.040% and 0.096%, respectively (not tabulated), which is significantly lower than that for the full sample (0.136% and 0.183%, respectively (see Panel B of Table 3). We further investigate the total transaction value of sequenced transactions in a sequence. We find that CEO's (chairman's) total purchase value in a sequence of transactions equals 0.129% (0.195%), which is comparable to the average transaction value in the other transaction subsample: 0.137% (0.190%) (not tabulated).

Panel D shows the market reactions to sequenced transactions considering their rank in the sequence.[25] For the subsample of sequenced purchases, the market reaction increases with the rank in the sequence: The CARs (0;1) of purchases of rank 2, 3, and higher are all significantly larger than for the first purchase in the sequence. For rank 3 and above, the market reactions (1.8% and 1.9%, respectively) are higher than those for the whole sample purchases (1.4% in Panel A). This pattern suggests that investors recognize sequenced transactions by the same director in multiple companies. For the sequenced sales subsample, we observe a similar pattern: The CARs (0;1) are more negative the higher their sales rank. We investigate the validity of alternative explanations for these patterns. First, directors may trade fewer shares at the beginning of a sequence due to uncertainty, and then increase the trading volume gradually. This explanation is supported for the sequenced purchase subsample as the value in GBP and the value as a percentage of market capitalization also increase with the rank (Panel D). However, for sequenced sales, this pattern does not hold. Second, directors may choose to trade first in the shares of larger companies and subsequently trade in the shares of smaller companies. Since market reactions may be stronger for smaller companies due to greater information asymmetry, this trading strategy would bank on the small company effect. However, when comparing the firm sizes across the transactions in a sequence, we do not find significant differences (last column of Panel D).

To sum up, as the sequence of transactions develops, more and more information is generated. Investors value subsequent transactions more than the first transaction, as the later transactions tend to confirm the trading opportunity revealed by the initial transaction. This supports conjecture 2. In addition, the transaction size goes up as the sequence of purchases develops, which may also explain the increase in market reaction.

[25] We have identified 989 sequences of sequenced transactions in our sample. The longest sequence contains 53 transactions. The mean (median) length of the sequences is three (two).

5.2 Mixed-effects models on the market reactions to insider trading

Opportunistic purchases and sales

As market reactions to insider trading may be influenced by director traits as well as firm characteristics, we apply a mixed-effects model and cluster standard errors at the company level. We examine whether the market reaction to the announcement of opportunistic insider purchases can be explained by the insider's network (as captured by the eigenvector centrality measure), as well as transaction and firm characteristics in column (1) of Table 6. We add the director's traits (i.e., position on the board, gender, and age) and the firm's internal governance characteristics in columns (2) and (3), and estimate the full model in column (4). In all specifications, director centrality is positively and significantly related to the market reaction (CAR(0;1)). In the model in column (4), for instance, a one standard-deviation increase in director centrality increases CAR(0;1) by 20 basis points. Our results support conjecture 1 as insider purchases carried out by better connected directors trigger a stronger market reaction, which suggests that the market believes that these directors are better informed.

Clustered and larger transactions trigger stronger market reactions, suggesting that multiple insider trades and larger trades give more credibility to the signal (columns (1) and (4)). Accounting for the position of the directors who trade (CEOs, chairmen, and former directors; treating executive, non-executive, and incoming directors as the base case), we do not find support for Seyhun's (1986) information hierarchy hypothesis as trades by CEOs and chairmen do not trigger stronger market reactions (columns (2) and (4)). The strong market reaction to the CEO and chairman transactions that we report in Table 5 can be explained by their larger trading values. Once the trading value is controlled for in the regressions, we no longer find that the insider trades of directors in the two top positions cause the greatest market reaction. Corporate governance variables, including CEO-chairman duality as well as the percentages of non-executive directors, female directors, and independent directors, do not affect the abnormal returns (columns (3) and (4)). Insider transactions cause stronger announcement reactions for smaller firms, possibly because information asymmetry is more severe for such firms (columns (1)-(4)), confirming the results of Seyhun (1986), Lakonishok and Lee (2001), Fidrmuc et al. (2006), Ravina and Sapienza (2010), and Cohen et al. (2012). Also in line with Fidrmuc et al. (2006), we find stronger market reactions for companies with greater director ownership, but weaker reactions for firms with ownership stakes held by corporations. Ownership concentration may affect the degree of asymmetric information between insiders and the market. Strong outside shareholders, who are likely to be active monitors (such as corporations), are expected to reduce agency costs, which decreases information asymmetries and in turn makes insider trading less informative. When directors own large share stakes, the inverse applies: stronger directors may reduce external monitoring, decrease the firm's transparency and make insider trading more informative.

We estimate the equivalent regressions for insider sales but do not find a relation between the market reactions to insider sales and the insiders' networks. If a sale occurs immediately before the close period, the market reacts more negatively. We also re-estimate the models for the routine transactions subsample only, and find that network strength fails to explain the market reaction to routine transactions.[26]

[Insert Table 6 about here]

Endogeneity issues

According to conjecture 1, access to non-firm-specific information allows directors to capture valuable trading opportunities. Therefore, their transactions carry more information and are followed by stronger market reactions. However, it is possible that some omitted factors contribute to both insider trading and the size of managerial networks. For example, a director of great ability or experience may be able to trade more effectively, and these qualities may also yield a successful career creating more opportunities to sit on other boards, which increases his centrality. As both the market reactions (CARs) and centrality may be affected by such omitted factors, we address this endogeneity issue in the models for opportunistic insider purchases (we did not find a relation for opportunistic sales) via the following two approaches.

First, we attempt to explicitly control for omitted factors. We measure a director's ability and experience by his past performance and tenure. Since non-executive directors are less responsible for the firm's performance, we focus on past performance of the companies where the director serves/has served as an executive director. We measure past performance by the average ROA in all the firms that the director has worked for (1) over all the past years since the beginning of the sample period, as well as (2) over the most recent three years. We measure a director's experience by (3) the total tenure over his whole managerial career (i.e., the total number of years he has held a managerial position in his current and former companies) and (4) his tenure as an executive director as experience at the board level may be more valuable. We use the above four measures of director ability and experience in our models to replace the eigenvector centrality measure and find that none is significantly related to the market reaction (not tabulated). We therefore conclude that transactions by directors of great ability or more experience do not contain more information value and that our observed positive relation between centrality and market reaction is not likely to only proxy for a director's past ability or experience.

Second, we apply an instrumental variable approach and search for instruments strongly correlated with eigenvector centrality but not with the dependent variable, such that the instrument only affects CARs through centrality. Inspired by Guedj and Barnea (2009) and Kini and Williams (2012), we use the industry average of board size and the industry average of the

[26] For reasons of parsimony, the results are not tabulated. The tables are available upon request.

eigenvector centrality measure as instruments for a director's eigenvector centrality. Both instruments are correlated with director eigenvector centrality but are not directly correlated with the market reactions to insider trades. We use a two-stage least squares (2SLS) random-effects regression: In the first stage, we regress centrality on the instruments and a set of control variables to derive the fitted values for centrality, and in the second stage, we regress the market reactions on the fitted values and control variables. We find significant and positive relations between centrality and the market reaction (column (5) of Table 6), which confirms our findings from columns (1) to (4) of Table 6[27].

Different CAR windows and clustered transactions

In Table 7, we further investigate the relation between eigenvector centrality and the market reaction. Column (2) is identical to the regression explaining CAR(0;1) in column (4) (the full model) of Table 6, whereas columns (1) and (3) of Table 7 show regressions with the dependent variable being based on the following different time windows: one month (20 trading days) prior to the insider transaction and 10 trading days subsequent to the transaction. We find no explanatory power of eigenvector centrality for the market response during the pre-announcement period and a weaker positive reaction – as compared to the (0;1) window – when we extend the announcement effect to the 10 days following the announcement day (which indicates that the market response is largely immediate). In the baseline regressions of Table 6, we control for clustered transactions by including a dummy variable capturing whether multiple transactions take place on the same day. In Table 7, we adopt a different perspective by focusing on (i) the largest transaction on each day (i.e., we exclude the other smaller transactions made on the same day – column (4)), and (ii) single transactions (i.e., we remove all transactions for which there is more than one transaction on the same day – column (5)). For these subsamples, we observe that director eigenvector centrality significantly increases the market reaction (CAR (0;1)). We conclude that the results are not induced by intra-day clustering of transactions and that our results from Table 6 are confirmed.[28]

[Insert Table 7 about here]

Alternative centrality measures

We study alternative centrality measures such as degree, closeness, and betweenness. Compared to the eigenvector centrality measure used in the baseline regression, these alternative measures focus on specific aspects of a director's connectivity and are therefore less

[27] Beside the endogeneity issue mentioned above, another alternative explanation is that better connected directors follow a different trading strategy than poorly connected directors in terms of timing their trades, but we do not find any timing differences between the types of directors.

[28] We did not find a relation between opportunistic sales and centrality. When we re-estimate the specifications shown in Table 7 for opportunistic sales, the market reaction and centrality remain unrelated.

comprehensive. More specifically, degree counts a director's number of adjacent direct connections to colleagues sitting on the same board. Both closeness and betweenness evaluate a director's network position in relation to other vertices and can be considered indirect measures of the information gathering potential of a director (Renneboog and Zhao, 2011): Closeness reflects the average geodesic distance to all other vertices in the network and betweenness measures how often a director may act as an information broker between other directors. Table 8 presents the models with the new centrality measures, and the same control variables and fixed effects as in the baseline regression (column (4) of Table 6). We conclude that director connections, captured by the normalized degree, eigenvector centrality, and betweenness are also positively and significantly related to how an insider transaction is received by the market. Only, closeness is insignificant. Eigenvector and degree centrality measures focus on direct connections (and eigenvector centrality weighs the relative importance of the directly connected nodes), while betweenness and closeness evaluate indirect connections (to nodes which are at a distance). The stronger results for the former type of centrality measures imply that first-hand information may be more valuable than information transmitted through (many) distant people. Furthermore, the direct connections are the ones immediately recognizable by the market participants as the direct connections are based on the executive and non-executive multiple directorships that a director holds, whereas indirect connections which can capture information transmission throughout the whole network are not directly observable by the market. The impact of direct or adjacent connections is also reported in Berkman et al. (2017). They investigate the whole trading portfolio of Finnish directors whose trading in firms in which they hold an executive and non-executive directorship triggers abnormal returns whereas their trades in firms in which they do not hold a management or supervisory positions do not lead to any abnormal returns.

It should also be noted that companies in large industries have more opportunities to be connected with other within-industry firms. Consequently, these firms could have higher centrality scores which entails that comparing centrality measures across industries may be biased. Therefore, we calculate an industry-adjusted centrality measure as the ratio of an individual centrality measure and the industry median centrality measure (determined on an annual basis). In column (4) of Table 8, we show that this industry-adjusted centrality measure is also significantly positively related to a trade's market reaction, which confirms our findings in the baseline regressions.

[Insert Table 8 about here]

Takeover activity

We expect that insider transactions in the acquiring company preceding M&A announcements have greater informational value and thus trigger stronger market reactions. For instance, Akbulut (2005) reports that managers of acquiring companies take advantage of their insider information by selling their shares prior to a stock merger (which is followed by negative abnormal returns for about half of the bidding firms). Agrawal and Nasser (2012) document an abnormal increase in net purchases of target company shares by registered insiders of target firms. Therefore, we investigate whether takeover activity before insider transactions (we use windows of 7, 30, and 180 days before day 0) influences the market reaction to insiders' opportunistic share purchases in the bidding company. We also examine insider trading subsequent to M&A transactions (using windows of the same length as above but covering the days following day 0). Table 9 shows that takeover activity before insider trades has no impact on the relation between a director's connectedness and the announcement returns. The response to a director's purchase within a week after a takeover announcement is significantly lower, which suggests that the market shifts its attention to the more influential event, i.e., the takeover announcement. Nevertheless, eigenvector centrality is significant in all six regressions and the negative effect of takeover activity in column (4) is relatively minor.

[Insert Table 9 about here]

Option-related purchases

Table 10 distinguishes between purchase transactions related to option exercises and all other transactions. For the option-related insider purchases (column (1)), the market reaction is unrelated to the centrality measure. The results for non-option related purchases are similar to those from the baseline regression in Table 6 (column (2)). This suggests that option-related insider transactions are less informative than the regular insider transactions, possibly because such transactions are driven by the characteristics of directors' incentive schemes rather than insider information.

[Insert Table 10 about here]

5.3 Insider trading frequency and value

While the analysis in Subsections 5.1 and 5.2 focused on the market reaction to individual transactions, we now study the effect of centrality on the trading activity of a director (measured by his trading frequency and the value of his trades) during each year. The sample used in this section is considerably larger because it includes both the directors who trade and those who do not trade (17% and 83% of the directors, respectively). Considering the distribution of the two dependent variables, we estimate random-effects Poisson regressions for trading frequency and random-effects Tobit regressions with left censoring at zero for trading value (Table 11). We classify all transactions into the following four categories: (i) opportunistic purchases, (ii) opportunistic sales, (iii) routine purchases, and (iv) routine sales.

Table 11 reveals that eigenvector centrality is strongly and negatively correlated with the number of both opportunistic purchases and sales (columns (1) and (2)). This implies that more informed directors (as proxied by network strength) trade less, but when they do they trigger a bigger market reaction (see Section 5.2). We also find that eigenvector centrality is strongly and negatively correlated with the value of both opportunistic purchases and sales (columns (3) and (4)). This provides support for conjecture 4.

We do not find evidence that routine trading frequency and value are related to connectedness (not tabulated). In addition, the eigenvector centrality is not significantly related to the value of routine trades (not tabulated).

Table 11 also suggests that male and younger directors trade more frequently and for higher values, consistent with Inci, Narayanan and Seyhun (2017). Directors who leave make fewer purchases and purchases of smaller value, and make more sales of higher value. The CEOs frequently make purchases and sales of higher value, whereas former directors trade the least. As to the measures of board structure, there is more frequent insider trading in companies with a smaller percentage of non-executive directors and without CEO-chairman duality. Finally, there is more frequent and more valuable trading in larger firms and those with higher accounting performance.

[Insert Table 11 about here]

When we re-estimate models (1) and (2) as a robustness test by means of zero-inflated Poisson regressions, we obtain very similar results (not tabulated) to those from the regular Poisson regressions. As a further robustness test, we verify whether our conclusions hold for the subsample of directors who trade. In other words, we exclude all directors who don't make any transactions. We re-estimate the regressions of Table 11 and the results are similar (not tabulated). We further verify the robustness of our results by means of alternative centrality measures (see Table 12): The normalized degree and betweenness measures are negatively and significantly related to the number as well as the value of opportunistic purchases and sales, which confirms the above conclusions.

[Insert Table 12 about here]

To sum up, directors with superior positions in director networks trade less frequently on an annual basis and trade lower values. This pattern is observed for the opportunistic transactions, but not for the routine transactions, which implies that conjecture 3 is rejected but conjecture 4 is not. Well-connected directors have better access to information and are therefore better able to select trading opportunities. Given that their transactions may also be more closely scrutinized by the market and regulators, better-connected directors may also trade more selectively.

5.4 *Profits and avoided losses from insider trading*

We measure the insider trading profit from purchasing shares by the value of the transaction (in GBP) multiplied by the abnormal stock return (as per Skaife, Veenman and Wangerin, 2013 and Cziraki and Gider, 2018). For sales, we use the loss avoided, defined as the negative transaction value multiplied by the abnormal stock return. We present the descriptive statistics for the insider trading profit in Table 13: Opportunistic purchases (sales) generate higher profits (greater losses avoided) than their routine counterparts. Due to their high transaction values (see Panel A of Table 2), opportunistic sales generate the highest gains (i.e., losses avoided).[29]

[Insert Table 13 about here]

We examine what explains the aggregate profit earned by an individual director over a given year (column (1) Table 14), as well as the profit earned from the routine transactions only (column (2)) and opportunistic transactions only (column (3)). We confirm that better-connected directors are better able to capture profitable trading opportunities and earn higher profits from insider trading. Furthermore, network strength affects the profitability of opportunistic transactions only. We examine trading profits coming from opportunistic purchases and sales (columns (4) and (5)) and find that insider profits are predominantly derived from purchases. Taken together with the results from the previous sections, we conclude that purchase transactions by well-connected directors generate stronger market reactions (Section 5.2). Although they trade less frequently and for smaller transaction values (Section 5.3), their trades are more profitable. They outperform directors with inferior networks in terms of trading profit (based on annual total profit), which fails to reject conjecture 4.

[Insert Table 14 about here]

To measure the profit earned from insider trading, some US studies use longer event windows (Lakonishok and Lee, 2001; Skaife et al., 2013 and El-Khatib, Jandik and Jandik, 2017) since the SEC Act of 1934 Section 16(b) prohibits short-swing profits (profits realized in any period of less than six months) by insiders in their own corporation's stock. In the UK, where there is no short-swing profits rule, the time between a buy and sell as well as a sell and a buy is much shorter (the median is 22 days). Therefore, we use short-run abnormal returns multiplied by transaction value (in GBP) to measure the profit made or loss avoided. We also estimated profit with longer event windows (e.g., 10 days) (not tabulated). The relation between explanatory variables (including centrality measure) and profit becomes weaker as event window extends. This observation can be explained by two reasons. First, non-firm-specific information is valuable in a limited period of time such that the profit opportunity soon disappears after the information revelation. Second, a longer event window likely includes noise induced by other transactions, information disclosure, or announcements, which may bias the measurement of insider trading profits.

6. Conclusion

This paper presents evidence that directors' connections affect their trading behavior as

[29] The positive profit for opportunistic sales indicates that the latter successfully avoid losses, whereas the negative profit of routine sales suggests that share prices often increase following routine sales, which generates losses for the director.

well as the market response to their transactions. By means of a unique dataset of insider transactions by and board connections among executive and non-executive directors in the UK, we find that well-connected directors trade less frequently and smaller transaction values than worse-connected directors and those further away from the center of the network. Moreover, the transactions of well-connected directors, especially the opportunistic (or non-routine) purchases, trigger stronger market reactions and yield higher profits.

This paper bridges the literature on insider trading and that on (graph-theoretical) network analysis. More specifically, we offer two new and important insights. First, while many extant studies focus on an insider's access to firm-specific information, we argue that an insider's connections extend his informational advantage beyond firm-specific information. This extended informational advantage may be derived from information about peers, industries, and the economy as a whole. We show that insider trades by directors with better access to information (proxied by various network centrality measures) trigger stronger market reactions. We also find that the market reaction to trades by well-connected directors becomes stronger for the later transactions if a director carries out a sequence of trades in the various firms where he holds board seats.

Second, well-connected directors likely have better trading opportunities and may therefore adopt a more selective trading strategy as reflected by less frequent trades and smaller transaction values. Even though they trade smaller values, well-connected directors still outperform other directors in terms of annually aggregated trading performance.

We control for a large number of factors that potentially affect insider trading behavior such as transaction size, insider position, firm characteristics, and ownership structure. The results are robust to alternative estimation techniques (mixed-effects regression models, the instrumental variables approach, panel GLS/zero-inflated Poisson regressions, and Tobit regressions), alternative network measures (normalized eigenvector centrality, degree, and betweenness), market reactions measured over different event windows and for a variety of subsamples (opportunistic and routine transaction subsamples, option related and non-option related transactions, clustered and unique transactions, trading director subsamples).

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Figure 1. An example of a network

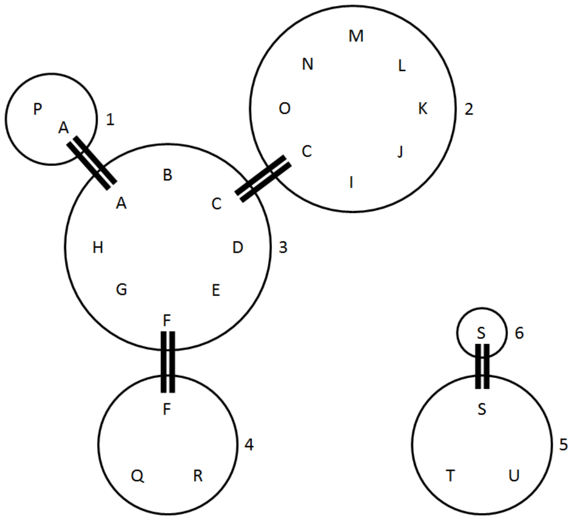

Figure 2. Insider Trading over Time

This figure shows the total value of insider purchases and sales (in million GBP) on an annual basis (left axis) and the number of routine transactions (right axis) as a percentage of the number of all transactions.

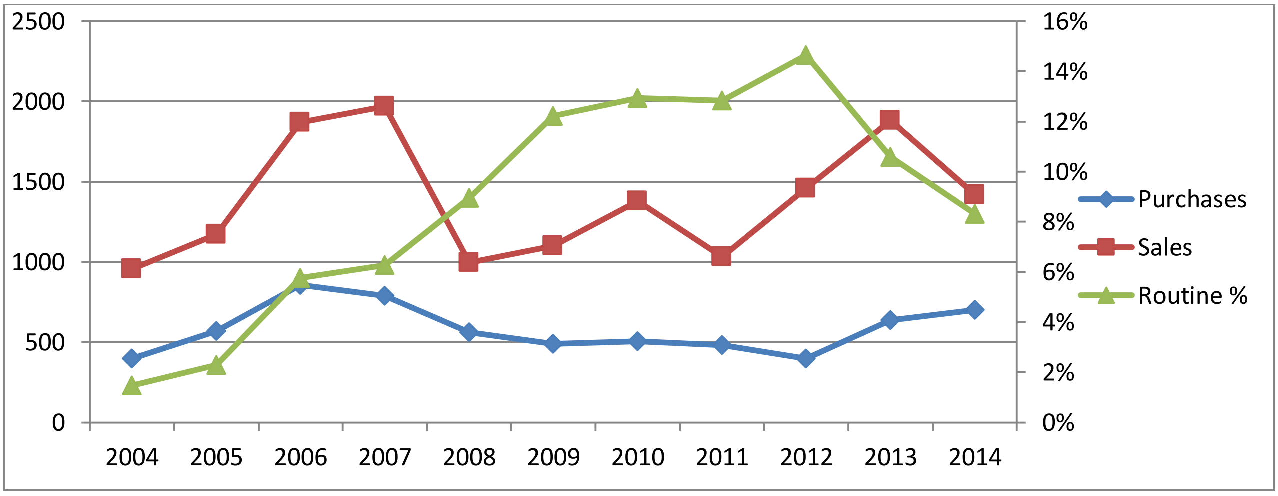

Table 1. Example of Trading Sequences in Connected Firms

Trading sequences consist of sequences of trades made within a 30-day period by the same director in the shares of the companies on whose board he sits. The table shows two examples of such trading sequences made by a same director. The variable *Purchase* equals one if the transaction is a purchase transaction, and zero otherwise. We assign *ranks* to each transaction based on its order within the sequence. When two transactions take place on the same day, they are assigned the same rank. In order to label a transaction as a 'same' or 'reverse' transaction, we first calculate the average past direction of the sequence over the past 30 days allotting a one to a purchase and a zero to a sale, unless the purchase or sale is the first transaction in the sequence. For example, for transaction 4 on May 24, 2013, three transactions (1, 2 and 3) took place within the previous 30 days, two purchases and one sale. Therefore, the average past transaction direction is 2/3 = 0.666. We subsequently calculate the difference between the direction of transaction 4 on May 24, 2013 (one as it is a purchase) and the average past transaction direction (0.666). We conclude that transaction 4 is 0.333 different from the average past transactions in terms of its direction. If the difference is smaller than 0.5, we consider that this transaction is in the same direction as past transactions (*connected-same*). If it is larger than 0.5, the transaction is in the opposite direction to past transactions (*connected-opposite*). If the gap is precisely 0.5, we consider it is a mixed case (*connected-mixed*). Additionally, a sequence can exceed 30 days (e.g., sequence 141 below), as long as the gap between any two consecutive transactions is less than 30 days.

Transaction ID	Company name	Date	Purchase	Sequence	Rank	Avg. past transaction direction	Change in direction	Sequenced direction
1	F	Apr 25, 2013	1	140	1			
2	S	Apr 29, 2013	1	140	2	1	0	same
3	A	May 1, 2013	0	140	3	1	1	opposite
4	F	May 24, 2013	1	140	4	0.666	0.333	same
5	A	Dec 2, 2013	0	141	1			
6	A	Dec 2, 2013	0	141	1			
7	S	Dec 23, 2013	1	141	2	0	1	opposite
8	A	Jan 21, 2014	1	141	3	1	0	same
9	A	Jan 21, 2014	0	141	3	1	1	opposite

Table 2. Insider Trading Frequency

This table presents descriptive statistics for the types of transactions (Panel A) and transactions by insider position (Panel B). Transaction types are categorized as purchases (purchases, contract buys, and option exercises) and sales (sales and sales post-exercise). Transactions taking place during the same month over three consecutive years are defined as routine transactions, while non-routine transactions are defined as opportunistic transactions. Insider positions include the CEO (including an executive chairman), other executive directors, non-executive chairmen, other non-executive directors, incoming directors, and former directors (i.e., directors who left the board in the financial year preceding the insider trade).

Panel A: Purchases, sales, opportunistic and routine transactions

Purchases		
Transaction Type	Frequency	Percent
Purchases	11,220	43.8
Contract Buys	3,653	14.2
Option Exercises	3,957	15.4
Sales		
Transaction Type	Frequency	Percent
Sales	2,509	9.8
Sales Post-Exercise	4,305	16.8
Total (Purchases and Sales)	25,644	100

Opportunistic and routine transactions		
Transaction Type	Frequency	Percent
Opportunistic purchases	16,985	66.2
Routine purchases	1,845	7.2
Opportunistic sales	5,981	23.3
Routine sales	833	3.2
Total	25,644	100

Panel B: Frequency of transactions by insider position

Purchases		
Insider positions	Frequency	Percent
CEO (including exec. chairman)	3,401	18.1
Other executive directors (excl. CEO)	5,616	29.8
Non-executive chairman	3,104	16.5
Other non-exec. directors (excl. non-exec. chairman)	5,596	29.7
Incoming director	895	4.8
Former director	218	1.2
Total	18,830	100
Sales		
Insider positions	Frequency	Percent
CEO (including exec. chairman)	1,782	26.2
Other executive directors (excl. CEO)	3,504	51.4
Non-executive chairman	502	7.4
Other non-exec. directors (excl. non-exec, chairman)	765	11.2
Incoming director	143	2.1
Former director	118	1.7
Total	6,814	100

Table 3. Insider Trading Stake Value

This table presents descriptive statistics by insider transaction type (Panel A) and insider position (Panel B). Value is measured in GBP (share price multiplied by number of shares traded) and the percentage of market capitalization stands for the number of shares traded divided by all shares outstanding. All values are winsorized at the first and 99th percentiles.

Panel A: Number of shares and value of purchases, sales, and opportunistic and routine transactions

Purchases						
Variable	N	Mean	Std. Dev	Min	Median	Max
Number of shares traded	18,828	169,306	450,920	145	22,500	2,800,000
Value (in GBP)	18,828	100,838	288,905	1,100	16,121	2,029,047
Value (% market capitalization)	18,828	0.102	0.279	0.001	0.020	1.950

Sales						
Variable	N	Mean	Std. Dev	Min	Median	Max
Number of shares traded	6,814	328,641	814,537	470	63,920	5,000,000
Value (in GBP)	6,814	702,027	1,459,538	2,504	200,000	8,670,000
Value (% market capitalization)	6,814	0.221	0.558	0.001	0.030	3.110

Opportunistic and routine transaction value (% market capitalization)						
Variable	N	Mean	Std. Dev	Min	Median	Max
Opportunistic purchases	16,983	0.111	0.290	0.000	0.020	1.950
Routine purchases	1,845	0.025	0.100	0.000	0.000	1.950
Opportunistic sales	5,981	0.245	0.587	0.000	0.030	3.110
Routine sales	833	0.050	0.192	0.000	0.010	2.230

Panel B: Value of transactions by insider position

Purchases value (% market capitalization)						
Variable	N	Mean	Std. Dev	Min	Median	Max
CEO	3,401	0.136	0.317	0.000	0.030	1.950
Other executive directors	5,616	0.076	0.212	0.000	0.010	1.950
Non-executive chairman	3,104	0.175	0.379	0.000	0.040	1.950
Other non-executive directors	5,594	0.078	0.253	0.000	0.010	1.950
Incoming	895	0.046	0.159	0.000	0.010	1.950
Former	218	0.072	0.241	0.000	0.001	1.950

Sales value (% market capitalization)						
Variable	N	Mean	Std. Dev	Min	Median	Max
CEO	1,782	0.240	0.571	0.000	0.040	3.110
Other executive directors	3,504	0.132	0.375	0.000	0.020	3.110
Non-executive chairman	502	0.439	0.805	0.000	0.080	3.110
Other non-executive directors	765	0.484	0.866	0.000	0.090	3.110
Incoming	143	0.039	0.090	0.000	0.010	0.700
Former	118	0.181	0.583	0.000	0.006	3.110

Table 4. Centrality Measures and Control Variables

This table reports centrality measures, namely degree, eigenvector centrality, closeness centrality and betweenness centrality. Centrality measures are calculated based on networks including all directors. We normalize centrality measures by the size of the whole network in the year. Statistics are based on the subsample of directors with trades.

Panel A: Centrality measures

Centrality measures						
Variable	N	Mean	Std. Dev	Min	Median	Max
Degree	25,644	12.33	7.041	3	10	56
Degree (normalized)	25,644	0.001	0.001	0.000	0.001	0.005
Eigenvector (normalized)	25,644	0.071	0.095	0.001	0.037	1.000
Closeness (normalized)	25,644	5.579	2.319	1.000	6.022	15.133
Betweenness (normalized)	25,644	0.001	0.002	0.000	0.000	0.036

Panel B: Control Variables

Control variables						
Variable	N	Mean	Std. Dev	Min	Median	Max
Male	25,642	0.944	0.231	0	1	1
Age	25,642	53.685	8.451	25	53	91
Leaving (before retirement)	22999	0.116	0.320	0	0	1
Leaving (retirement)	22999	0.017	0.131	0	0	1
CEO	25642	0.202	0.402	0	0	1
Chairman	25642	0.148	0.355	0	0	1
Former directors	25642	0.013	0.114	0	0	1
% non-executives	25143	0.573	0.144	0	0.6	1
% female	25143	0.081	0.103	0	0	0.6
Duality	25143	0.048	0.214	0	0	1
ROA (%)	25,642	3.910	11.158	-23.350	6.140	20.720
Debt ratio (%)	25,642	18.195	17.007	0.000	15.020	57.150
EBIT/interest	23,095	14.576	20.803	-4.681	6.201	61.951
Fixed assets ratio (%)	25,584	24.783	26.447	0.176	13.831	84.569
Payout ratio	20,303	0.322	0.252	0.000	0.318	0.986
(Log) total assets	25,642	19.227	2.403	9.473	19.147	26.322
Director ownership	23,009	0.000	0.001	0.000	0.000	0.003
Family ownership	23,009	0.078	0.130	0.000	0.033	0.715
Institutional ownership	23,009	0.565	0.261	0.000	0.602	1
Company ownership	23,009	0.098	0.127	0.000	0.061	0.683
Government ownership	23,009	0.006	0.013	0.000	0.000	0.108
Other ownership	23,009	0.007	0.023	0.000	0.000	0.166

Table 5. Market Reactions to Insider Transactions

This table presents descriptive statistics of the market reactions measured over a variety of event windows ((-20;-1), (0;1), (0;5) and (0;10)) by transaction type in Panel A. The market reactions to transactions by insider position are presented in Panel B. Panels C and D report the market reactions to sequenced transactions. All values are winsorized at the first and 99^{th} percentiles.

Panel A: Market reactions to transactions by event window and transaction type

Variable	N	Mean	Std. Dev	Min	Median	Max	p-value
Market reaction to purchases							
CAR (-20;-1)	18,328	-0.011	0.131	-0.367	-0.008	0.366	0.000
CAR (0;1)	18,345	0.014	0.052	-0.091	0.003	0.204	0.000
CAR (0;5)	18,345	0.018	0.072	-0.131	0.006	0.266	0.000
CAR (0;10)	18,345	0.020	0.092	-0.180	0.006	0.318	0.000
Market reaction to sales							
CAR (-20;-1)	6,724	0.006	0.085	-0.367	0.002	0.366	0.000
CAR (0;1)	6,725	-0.002	0.030	-0.091	-0.001	0.204	0.000
CAR (0;5)	6,725	-0.003	0.043	-0.131	-0.002	0.266	0.000
CAR (0;10)	6,725	-0.007	0.058	-0.180	-0.007	0.318	0.000
Market reaction to opportunistic and routine trades (CAR (0;1))							
Opportunistic purchases	16,560	0.015	0.054	-0.091	0.004	0.204	0.000
Routine purchases	1,785	0.004	0.036	-0.091	0.000	0.204	0.000
Opportunistic sales	5,900	-0.002	0.031	-0.091	-0.002	0.204	0.000
Routine sales	825	0.001	0.021	-0.091	0.001	0.088	0.198

Panel B: Market reactions to transaction by insider position

Variable	N	Mean	Std. Dev	Min	Median	Max	p-value
Market reaction to purchases (CAR (0;1))							
CEO	3,336	0.017	0.056	-0.091	0.004	0.204	0.000
Other executive directors	5,539	0.012	0.050	-0.091	0.002	0.204	0.000
Non-executive Chairman	3,010	0.021	0.060	-0.091	0.006	0.204	0.000
Other non-executive directors	5,361	0.013	0.050	-0.091	0.003	0.204	0.000
Incoming	885	0.006	0.039	-0.091	0.001	0.204	0.000
Former	214	0.011	0.052	-0.091	0.002	0.204	0.003
Market reaction to sales (CAR (0;1))							
CEO	1,751	-0.001	0.029	-0.091	-0.001	0.168	0.127
Other executive directors	3,470	-0.001	0.027	-0.091	-0.001	0.204	0.026
Non-executive Chairman	496	-0.005	0.033	-0.091	-0.004	0.163	0.001
Other non-executive directors	749	-0.003	0.041	-0.091	-0.004	0.204	0.024
Incoming	142	0.000	0.025	-0.091	-0.001	0.113	0.868
Former	117	0.002	0.034	-0.074	-0.001	0.204	0.492

Panel C: Market reactions to sequenced transactions

Variable	N	Mean	Std. Dev	Min	Median	Max	p-value
Market reaction to purchases (CAR (0;1))							
Sequenced-same	259	0.012	0.063	-0.434	0.004	0.307	0.003
Sequenced -mixed	25	0.008	0.045	-0.037	-0.004	0.166	0.369
Sequenced -opposite	55	0.014	0.065	-0.219	0.003	0.281	0.123
Market reaction to sales (CAR (0;1))							
Sequenced -same	21	-0.017	0.048	-0.110	-0.009	0.088	0.126
Sequenced -opposite	43	-0.007	0.042	-0.211	-0.006	0.076	0.294
Market reaction to purchases (CAR (0;1)) Sequenced -same by type of director							
CEO	46	0.005	0.058	-0.091	-0.002	0.204	0.552
Other executive directors	49	-0.001	0.036	-0.075	-0.004	0.123	0.911
Chairman	198	0.016	0.056	-0.091	0.003	0.204	0.000
Other non-executive directors	301	0.007	0.036	-0.091	0.002	0.204	0.001
Incoming	45	-0.003	0.022	-0.073	-0.001	0.040	0.375
Former	5	0.005	0.039	-0.036	-0.001	0.070	0.775

Panel D: Market reactions to sequenced transactions by ranks

Sequenced purchases							
Rank	N	Number of shares traded	Value (in GBP)	Value (% market capitalization)	CAR (0;1)	p-value (relative to first transaction)	(ln) total assets
1	251	125,678	74,581	0.062	0.006		19.843
2	259	95,828	98,271	0.071	0.011	0.071	20.046
3	44	174,181	127,549	0.156	0.018	0.097	19.945
4+	38	187,901	194,082	0.157	0.019	0.064	19.650
Sequenced sales							
Rank	N	Number of shares traded	Value (in GBP)	Value (% market capitalization)	CAR (0;1)	p-value (relative to first transaction)	(ln) total assets
1	66	511,613	1,107,642	0.244	-0.003		19.878
2	52	732,417	1,073,995	0.445	-0.007	0.284	20.296
3	11	166,763	526,307	0.091	-0.022	0.055	19.643

Table 6. Market Reaction to Opportunistic Purchases

This table presents the mixed-effects regressions explaining the market reaction to opportunistic trades, as CAR (0;1), by the centrality measure and other variables. The centrality measure is the eigenvector centrality score of the trading director. We control for transaction characteristics, director traits, board characteristics, ownership structure, time and industry fixed effects. Detailed variable definitions are given in Appendix 1. Standard errors are clustered at the firm level and reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Dependent variable: CAR (0;1)	(1)	(2)	(3)	(4)	(5) 2nd stage IV
Eigenvector centrality	0.028**	0.021*	0.025**	0.025**	0.056*
	(0.012)	(0.011)	(0.011)	(0.012)	(0.031)
Transaction characteristics					
Value (% market capitalization)	0.008***	0.007***	0.008***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Clustered trade	0.005**			0.005**	0.006***
	(0.002)			(0.002)	(0.001)
Sequenced trade	-0.003			-0.004	-0.006
	(0.003)			(0.003)	(0.004)
Before close	0.001			-0.000	-0.001
	(0.005)			(0.005)	(0.004)
After close	0.005			0.001	-0.000
	(0.004)			(0.003)	(0.002)
Director traits					
Male		0.003		0.003	0.004
		(0.002)		(0.002)	(0.003)
Age		0.000		0.000	0.000**
		(0.000)		(0.000)	(0.000)
CEO		0.000		-0.000	0.001
		(0.001)		(0.002)	(0.002)
Chairman		0.001		0.001	0.001
		(0.002)		(0.002)	(0.002)
Former directors		0.000		0.000	0.001
		(0.004)		(0.004)	(0.006)
Board characteristics					
% non-executives			0.011	0.007	0.003
			(0.011)	(0.011)	(0.006)
% female			-0.010	-0.003	-0.003
			(0.013)	(0.013)	(0.008)
Duality			0.006	0.006	0.004
			(0.007)	(0.007)	(0.004)
Firm characteristics					
ROA	-0.000	-0.000	-0.000	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Debt ratio	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBIT/interest	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed assets ratio	0.000	0.000	0.000	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Payout ratio	-0.001	-0.001*	-0.001*	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
(Log) total assets	-0.006***	-0.005***	-0.006***	-0.005***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ownership structure					
Director ownership	0.179**	0.173**	0.182**	0.182**	0.131**
	(0.088)	(0.085)	(0.086)	(0.088)	(0.064)
Family ownership	-0.005	-0.004	-0.006	-0.004	-0.003
	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)
Institutional ownership	0.009	0.008	0.009	0.009	0.007**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.003)
Company ownership	-0.013*	-0.014**	-0.014*	-0.014**	-0.016***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Government ownership	0.006	0.003	0.012	0.007	-0.026
	(0.036)	(0.036)	(0.037)	(0.036)	(0.044)
Other ownership	0.018	0.018	0.020	0.017	0.021
	(0.022)	(0.021)	(0.021)	(0.022)	(0.020)
Constant	0.108***	0.091***	0.105***	0.087***	0.093***
	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.680	0.683	0.685	0.688	0.045
N	10275	10021	10151	9912	10183

Table 7. Market Reaction to Opportunistic Purchases: Alternative CAR Windows and Transaction Subsamples

This table presents the mixed-effects regression explaining the market reaction to opportunistic purchases, as measured by CAR (-20;-1), CAR (0;1) and CAR (0;10) , by the centrality measure and other variables. While the sample used in columns (1)-(3) is the full sample of all opportunistic purchases, columns (4)-(5) focus on the subsamples that comprise only (i) the largest transaction on each day, and (ii) single transactions (i.e., we remove all transactions for which there is at least one other transaction on the same day. The centrality measure is the eigenvector centrality score of the trading director. We control for transaction characteristics, director traits, board characteristics, ownership structure, time and industry fixed effects. Detailed variable definitions can be found in Appendix 1. Standard errors are clustered at the firm level and reported in parentheses. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent variables:	CAR (-20;-1)	CAR (0;1)	CAR (0;10)	CAR (0;1) Daily largest only	CAR (0;1) Single transactions only
Eigenvector centrality	-0.011	0.025**	0.036*	0.023**	0.021*
	(0.020)	(0.012)	(0.023)	(0.011)	(0.012)
Value (% market capitalization)	0.001	0.008***	0.009**	0.008***	0.006***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Controls					
Transaction characteristics	Yes	Yes	Yes	Yes	Yes
Director traits	Yes	Yes	Yes	Yes	Yes
Board characteristics	Yes	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes
Ownership structure	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.422	0.662	0.585	0.650	0.659
N	9912	9912	9912	6786	5271

Table 8. Market Reaction to Opportunistic Purchases: Alternative Centrality Measures

This table presents the mixed-effects regressions explaining the market reaction to opportunistic purchases, as measured by CAR (0;1), by alternative centrality measures (normalized degree, normalized betweenness, normalized closeness, and industry adjusted eigenvector centrality) of the trading director. We control for transaction characteristics, director traits, board characteristics, ownership structure, time and industry fixed effects. Detailed variable definitions can be found in Appendix 1. Standard errors are clustered at the firm level and reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ∗∗∗, ∗∗, and ∗, respectively.

Dependent: CAR (0;1)	(1)	(2)	(3)	(4)
Degree (normalized)	2.384**			
	(1.199)			
Betweenness (normalized)		0.437*		
		(0.268)		
Closeness (normalized)			0.001	
			(0.001)	
Eigenvector centrality (industry adjusted)				0.001***
				(0.000)
Controls				
Transaction characteristics	Yes	Yes	Yes	Yes
Director traits	Yes	Yes	Yes	Yes
Board characteristics	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes
Ownership structure	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Pseudo R^2	0.687	0.688	0.688	0.687
N	9912	9912	9912	10183

Table 9. Market Reaction to Opportunistic Purchases: Takeover Event Timing

This table presents the mixed-effects regression explaining the market reaction (CAR (0;1)) to opportunistic purchases in bidding company by the centrality measure, number of takeover events before and after the insider transaction and other control variables. The centrality measure is the eigenvector centrality score of the trading director. We control for transaction characteristics, director traits, board characteristics, ownership structure, time and industry fixed effects. Detailed variable definitions can be found in Appendix 1. Standard errors are clustered at the firm level and reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Dependent variable: CAR (0;1)	(1)	(2)	(3)	(4)	(5)	(6)
Eigenvector centrality	0.025**	0.025**	0.024**	0.024**	0.025**	0.025**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Value (% market Capitalization)	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of M&As 7 days before	0.000					
	(0.006)					
Number of M&As 30 days before		-0.001				
		(0.002)				
Number of M&As 180 days before			-0.001			
			(0.001)			
Number of M&As 7 days after				-0.007**		
				(0.004)		
Number of M&As 30 days after					-0.001	
					(0.002)	
Number of M&As 180 days after						-0.001
						(0.001)
Controls						
Transaction characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Director traits	Yes	Yes	Yes	Yes	Yes	Yes
Board characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Ownership structure	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.688	0.688	0.687	0.687	0.688	0.687
N	9017	9017	9017	9017	9017	9017

Table 10. Market Reaction to Opportunistic Purchases: Option- and Non-option-related Transactions

This table presents the mixed-effects regression explaining the market reaction to opportunistic purchases, as measured by CAR (0;1), by the centrality measure and other variables. Regressions in columns (1) and (2) are based on the subsample of option-related transactions and non-option-related transactions, respectively. The dependent variable is cumulative abnormal return of day 0 and day 1. The centrality measure is the eigenvector centrality score of the trading director. We control for transaction characteristics, director traits, board characteristics, ownership structure, time and industry fixed effects. Detailed variable definitions can be found in Appendix 1. Standard errors are clustered at the firm level and reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ∗∗∗, ∗∗, and ∗, respectively.

Dependent variable: CAR (0;1)	(1) Option related purchases	(2) Non-option related purchases
Eigenvector centrality	-0.017	0.026**
	(0.010)	(0.012)
Value (% market capitalization)	0.002	0.009***
	(0.001)	(0.002)
Controls		
Transaction characteristics	Yes	Yes
Director traits	Yes	Yes
Board characteristics	Yes	Yes
Firm characteristics	Yes	Yes
Ownership structure	Yes	Yes
Time fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Pseudo R^2	0.884	0.782
N	2524	7659

Table 11. Insider Trading Activity – Transaction Frequency and Value

This table shows the relation between network centrality and, respectively, the frequency of opportunistic purchases and sales (random-effects GLS Poisson regressions) and the transaction value of those trades (GLS Tobit regressions with left censoring at zero). The centrality measure is the eigenvector centrality score of the trading director. We control for director traits, board characteristics, ownership structure, time and industry fixed effects. Detailed variable definitions can be found in Appendix 1. Standard errors are clustered at the firm level and reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ∗∗∗, ∗∗, and ∗, respectively.

Dependent variables:	(1) Number of opportunistic purchases	(2) Number of opportunistic sales	(3) Value of opportunistic purchases	(4) Value of opportunistic sales
	GLS Poisson	GLS Poisson	GLS Tobit	GLS Tobit
Eigenvector centrality	-0.649***	-2.035***	-5.752***	-22.859***
	(0.164)	(0.281)	(1.365)	(2.836)
Male	0.258***	0.781***	1.812***	9.416***
	(0.066)	(0.113)	(0.550)	(1.190)
Age	-0.020***	-0.028***	-0.198***	-0.336***
	(0.002)	(0.003)	(0.016)	(0.031)
Leaving (before retirement)	-0.082***	0.211***	-1.061***	2.226***
	(0.031)	(0.043)	(0.282)	(0.464)
Leaving (retirement)	-0.194***	0.084	-2.030***	1.821*
	(0.074)	(0.111)	(0.589)	(1.035)
CEO	0.531***	0.472***	5.128***	7.685***
	(0.039)	(0.057)	(0.350)	(0.602)
Chairman	0.279***	-0.059	2.309***	-0.015
	(0.040)	(0.067)	(0.343)	(0.676)
Former directors	-0.976***	-0.345***	-8.314***	-3.245***
	(0.041)	(0.051)	(0.321)	(0.505)
% non-executives	-0.271**	-0.914***	-2.876***	-10.734***
	(0.106)	(0.163)	(0.905)	(1.667)
% female	0.305**	-0.098	1.096	0.455
	(0.139)	(0.212)	(1.230)	(2.213)
Duality	-0.320***	-0.178*	-2.120***	-1.645*
	(0.066)	(0.095)	(0.538)	(0.964)
ROA	0.004***	0.029***	0.042***	0.290***
	(0.001)	(0.002)	(0.010)	(0.022)
Debt ratio	-0.000	-0.003**	-0.002	-0.033**
	(0.001)	(0.001)	(0.005)	(0.014)
EBIT/interest	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Fixed assets ratio	-0.000	0.000**	-0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Payout ratio	-0.014	0.006	-0.093	0.059
	(0.008)	(0.011)	(0.071)	(0.111)
Ln total assets	0.121***	0.243***	1.075***	2.339***
	(0.009)	(0.016)	(0.080)	(0.159)
Director ownership	-0.467	-2.971	-0.019	-44.379**
	(1.077)	(1.937)	(8.184)	(19.019)
Family ownership	-0.002	-0.047	-1.398*	-0.744
	(0.083)	(0.125)	(0.744)	(1.295)
Institutional ownership	0.012	0.112	1.188**	1.807**
	(0.056)	(0.083)	(0.485)	(0.858)
Company ownership	0.045	-0.030	-0.371	-1.310
	(0.089)	(0.133)	(0.791)	(1.384)
Government ownership	-3.051***	-3.458***	-16.079**	-29.772**
	(0.696)	(1.251)	(6.845)	(12.561)
Other ownership	-0.304	1.188***	-1.721	9.529**
	(0.328)	(0.425)	(2.838)	(4.632)
Time fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Pseudo R^2	0.103	0.125	0.053	0.065
N	42838	42838	42838	42838

Table 12. Trading Activity - Transaction Frequency and Value with Different Centrality Measures

This table shows the relation between network centrality and, respectively, the frequency of opportunistic purchases and sales (random-effects GLS Poisson regressions) and the transaction value of those trades (GLS Tobit regressions with left censoring at zero). The dependent variable is the annual total number (value) of transactions specified in each column title. The centrality measure is the degree and betweenness centrality score of the trading director. We control for director traits, board characteristics, ownership structure, time and industry fixed effects. Detailed variable definitions can be found in Appendix 1. Standard errors are clustered at the firm level and reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ∗∗∗, ∗∗, and ∗, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variables:	Number of opportunistic purchases	Number of opportunistic purchases	Number of opportunistic sales	Number of opportunistic sales	Value of opportunistic purchases	Value of opportunistic purchases	Value of opportunistic sales	Value of opportunistic sales
	GLS Poisson	GLS Poisson	GLS Poisson	GLS Poisson	GLS Tobit	GLS Tobit	GLS Tobit	GLS Tobit
Degree (normalized)	-120.208***		-402.641***		-739.940***		-4122.941***	
	(21.800)		(39.161)		(237.943)		(388.718)	
Betweenness (normalized)		-25.618***		-83.241***		-85.630		-879.294***
		(6.071)		(12.608)		(54.750)		(119.733)
Controls								
Director traits	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Board characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ownership structure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.104	0.103	0.130	0.127	0.054	0.053	0.067	0.065
N	42838	42838	42838	42838	42838	42838	42838	42838

Table 13. Profitability of Insider Transactions

This table presents descriptive statistics for the profit generated from various types of insider transactions. Profit is measured by the product of the abnormal market return (CAR (0;1), CAR (0;5) and CAR (0;10)) and transaction value in GBP (negative for sales). We report descriptive statistics of profit generated from opportunistic (routine) and purchase (sale) transactions.

Profit of insider transactions						
Variable	N	Mean	Std. Dev	Min	Median	Max
Profit (0;1) Opportunistic purchases	16,560	590	5,441	-21,724	37	29,159
Profit (0;5) Opportunistic purchases	16,560	738	7,702	-32,380	59	39,820
Profit (0;10) Opportunistic purchases	16,560	692	10,340	-45,485	61	51,908
Profit (0;1) Routine purchases	1,785	211	2,553	-10,459	0	17,571
Profit (0;5) Routine purchases	1,785	328	3,554	-12,762	0	25,398
Profit (0;10) Routine purchases	1,785	564	4,746	-15,643	6	33,275
Profit (0;1) Opportunistic sales	5,900	3,415	27,740	-80,622	92	136,997
Profit (0;5) Opportunistic sales	5,900	4,874	39,248	-118,602	189	191,259
Profit (0;10) Opportunistic sales	5,900	7,895	52,479	-150,113	502	260,750
Profit (0;1) Routine sales	825	-1,310	13,126	-67,240	-65	55,189
Profit (0;5) Routine sales	825	-1,964	21,622	-105,851	-146	76,208
Profit (0;10) Routine sales	825	-646	24,619	-102,933	139	98,575

Table 14. Insider Trading Profit

This table presents random-effects regressions explaining profit by the centrality measure and other variables. The dependent variable is the annual total profit of the type of transactions specified in each column title in parentheses. The centrality measure is the eigenvector centrality score of the trading director. We control for director traits, board characteristics, ownership structure, time and industry fixed effects. Detailed variable definitions can be found Appendix 1. Standard errors are clustered on firm level and reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ∗∗∗, ∗∗, and ∗, respectively.

Dependent variables:	(1) Annual profit (all)	(2) Annual profit (routine transactions)	(3) Annual profit (opportunistic transactions)	(4) Annual profit (opportunistic purchases)	(5) Annual profit (opportunistic sales)
Eigenvector centrality	2.654***	0.100	2.554***	2.938***	-0.384
	(1.012)	(0.419)	(0.924)	(0.797)	(0.619)
Value (% market capitalization)	0.097	-0.024*	0.121	0.153**	-0.032
	(0.118)	(0.012)	(0.119)	(0.062)	(0.096)
Male	0.695**	-0.028	0.723***	0.570**	0.153
	(0.288)	(0.110)	(0.268)	(0.240)	(0.195)
Age	0.016*	0.003	0.013	0.023***	-0.010
	(0.010)	(0.003)	(0.009)	(0.008)	(0.006)
% non-executives	0.629	0.297	0.332	0.177	0.155
	(0.615)	(0.182)	(0.598)	(0.545)	(0.382)
% female	-0.925	-0.750**	-0.175	-0.376	0.201
	(0.805)	(0.309)	(0.770)	(0.666)	(0.624)
Duality	0.769*	0.212	0.557	0.228	0.329
	(0.422)	(0.216)	(0.381)	(0.321)	(0.273)
ROA	-0.019*	-0.002	-0.017*	-0.016*	-0.001
	(0.010)	(0.004)	(0.010)	(0.009)	(0.007)
Debt ratio	-0.002	-0.006***	0.004	0.005	-0.001
	(0.005)	(0.002)	(0.004)	(0.004)	(0.003)
EBIT/interest	-0.000***	0.000	-0.000***	-0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed assets ratio	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Payout ratio	-0.188***	-0.050*	-0.139**	-0.066	-0.072
	(0.056)	(0.026)	(0.064)	(0.041)	(0.065)
(log) total assets	-0.422***	0.015	-0.437***	-0.396***	-0.041
	(0.053)	(0.021)	(0.049)	(0.043)	(0.035)
Director ownership	-0.323	-1.490	1.166	6.902	-5.735
	(7.651)	(2.562)	(7.424)	(6.748)	(5.127)
Family ownership	-0.363	0.287*	-0.650	-0.815*	0.165
	(0.519)	(0.172)	(0.509)	(0.457)	(0.387)
Institutional ownership	-0.351	-0.249**	-0.102	0.203	-0.306
	(0.293)	(0.109)	(0.281)	(0.248)	(0.216)
Company ownership	-1.703***	-0.820***	-0.883	-0.649	-0.234
	(0.605)	(0.268)	(0.561)	(0.502)	(0.507)
Government ownership	0.812	-1.445	2.257	-1.968	4.225**
	(3.286)	(1.205)	(3.220)	(2.667)	(1.907)
Other ownership	3.227	1.021	2.206	0.514	1.692
	(1.996)	(0.655)	(1.888)	(1.719)	(1.701)
Constant	8.334***	-0.189	8.523***	6.885***	1.638**
	(1.087)	(0.431)	(1.013)	(0.908)	(0.728)
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.002	0.005	0.021	0.025	0.002
N	11802	11802	11802	11802	11802

Appendix 1. Variable Definitions

Variable	Definition	Data Source
Eigenvector centrality	Baseline centrality measure. See Section 3.1 for details	Own calculations
Degree	Alterative centrality measure. See Section 3.1 for details	Own calculations
Betweenness	Alterative centrality measure. See Section 3.1 for details	Own calculations
Closeness	Alterative centrality measure. See Section 3.1 for details	Own calculations
	Transaction characteristics	
Trading value	Value of shares traded as a percentage of company's market value	Directors Deals
Clustered trade	=1 if two insider transactions of the same type (purchase or sale) occur in a company on the same day, =0 otherwise	Directors Deals
Sequenced trade	=1 if there is another transaction of the same type (purchase or sale) by the same director in another connected company within a period of 30 days, =0 otherwise	Directors Deals; BoardEX
Before close	=1 if the transaction happens less than seven days before the close period, =0 otherwise	Directors Deals; Datastream
After close	=1 if the transaction happens less than seven days after the close period, =0 otherwise	Directors Deals; Datastream
Number of M&As N days before	Number of M&A transactions the company has announced N days before the insider transaction in the bidding company.	SDC Platinum
Number of M&As N days after	Number of M&A transactions the company has announced N days after the insider transaction in the bidding company.	SDC Platinum
	Director traits	
CEO	=1 if the trading director is the CEO, =0 otherwise	BoardEX
Chairman	=1 if the trading director a non-executive chairman, =0 otherwise	BoardEX
Other executives	=1 if the trading director is an executive director (excluding the CEO), =0 otherwise	BoardEX
Other non-executives	=1 if the trading director is a non-executive director (excluding the chairman), =0 otherwise	BoardEX
Former directors	=1 if the trading director is a former director, =0 otherwise	BoardEX
Male	=1 if the trading director is male, =0 otherwise	BoardEX
Age	Age of the trading director	BoardEX
Leaving (before retirement)	=1 if the trading director is younger than 65 years and leaves the firm the year following his trade, =0 otherwise	BoardEX
Leaving (retirement)	=1 if the trading director is older than 65 and leaves the firm the year following the trade, =0 otherwise	BoardEX
	Board characteristics	
% non-executives	Percentage of non-executive directors on the board	BoardEX
% females	Percentage of female directors on the board	BoardEX
Duality	=1 if the positions of CEO and chairman are held by the same person, =0 otherwise	BoardEX
	Financial information	
ROA	Operating income divided by book value of total assets	Datastream
Debt ratio	Total liabilities divided by total assets	Datastream
EBIT interest ratio	EBIT divided by total interest expense	Datastream
Fixed assets/total assets	Fixed assets divided by total assets	Datastream
Dividend payout	Dividend divided by net income	Datastream
Total assets	Book value of total assets	Datastream
	Ownership structure	
Director ownership	Percentage of shares owned by the (executive and non-executive) directors	Osiris
Family ownership	Percentage of shares owned by family owners	Osiris
Institutional ownership	Percentage of shares owned by institutional investors	Osiris
Company ownership	Percentage of shares owned by companies	Osiris
Government ownership	Percentage of shares owned by the government	Osiris
Other ownership	Percentage of shares owned by other investors	Osiris

Appendix 2. Multiple board seats

This table reports the number of board seats held by insider position. The insider position is determined by the position the trading insider holds in the company whose shares he trades.

	Number of board seats			
Insider position	1	2	3	4+
CEO (including executive chairman)	4,250	823	97	13
Other executive directors (excl. CEO)	8,179	839	94	8
Non-executive chairman	1,931	776	443	456
Other non-exec. directors (excl. non-exec. chair)	3,958	1,417	569	417
Incoming directors	748	207	45	38
Former directors	256	55	18	7
Total	19,322	4,117	1,266	939

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