Insiders' trading on non-private information:

Evidence from their trading on their economically linked firms' M&A events

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Abstract

We propose using insider trading activity from economically linked firms as a novel measure to identify the sources of gains in M&A deals. We find that insiders trade profitably their own firms' shares when their economically linked companies become takeover targets. Their trades predict their firm's receiving takeover bid, and changes in its future operating and innovation efficiencies. The treatment effect is stronger when the target firm is producing homogeneous products and has a more complicated supply chain. We rule out the possibility that insiders are trading on their own firm's private information. Instead, our results imply that insiders have a better understanding of the impact of the deal on their firm than the aggregate market, which suffers from limited attention constraint bias.

Keywords: Mergers and acquisitions, economically linked firms, supply chain, insider trading
JEL Classification: G14, G11, G12, G34

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I. Introduction

Previous studies find that corporate insiders from both acquirer and target firms in a merger and acquisition (M&A) deal avoid actively trading in their own firms' shares on their private information because the SEC scrutinizes their trades to prevent illegal insider trading (Kacperczyk and Pagnotta, 2021). Instead, insiders maximize their personal gains without taking too much litigation risk by systematically selling less before M&A announcement to reap any M&A premium, (Agrawal and Nasser, 2012; Davis *et al*., 2022; Fidrmuc and Xia, 2022 and Chen *et al.,* 2022)[3]. However, research has not covered fully the trading behavior of insiders on public information, such as a takeover bid on their economically linked firms - their competitors and supply chain (customer and supplier) firms. We expect insiders to trade profitability, without significant potential litigation risks on such public announcements, because they are likely to better understand the implication of the takeover bid on their own firm as they are likely to have superior knowledge about the nature, the stability, and the condition of their economically linked firms. They are also likely to trade profitably on the limited attention constraint of the aggregate market, through its inability to fully understand the impact of the takeover bid of their supply chain firms (Cohen and Frazzini, 2008) and their competitors (Eisdorfer et al., 2022). Finally, their trading profitability may emanate from their ability to assess properly the likelihood that their firm becomes a takeover target in the future. Overall, we consider that the public M&A announcement of their economically linked firms allows us to better differentiate the information channel insiders are considering in their trading decision. Insider trading literature predominantly argue that corporate insiders are informed agents because they have private access to their own firms' future fundamental. Their trading on M&A announcement of their economically linked firms allows us to investigate whether corporate insiders can better understand public information than outside investors.

Figure 1 summarizes our research setting. We focus on the trading by insiders in insider trading (IT) firms after the announcement of takeover bids of their economically-connected companies – their competitors and/or supply chain firms (customers and suppliers). We specify that our IT firms have no link with the bidding firms to avoid confounding events. Therefore, for competitors, we include only targets with bidders from other industries than our IT firms.

[Insert Figure 1 here]

[3] For example, Eckbo (1983), Shenoy (2012) and Davis *et al.* (2021) provide a general review of the predominant theories regarding the source of merger gains.

We collect a sample of 685 U.S domestic deals announced from 2003, the start date of our supply-chain database FactSet Revere, to 2020. We then search the IT firms for which the target firms are the competitors, customers, and suppliers. We find 1,106 are competitors, 812 customers, and 598 suppliers. Next, we assess the behavior and trading profitability of insiders in their own IT firms in the next three months after their linked firms' M&A announcement month. We find that insiders abnormally sell less shares in their firms after their competitors or customers, but not suppliers, have become the target in an M&A deal, indicating that these insiders recognize their firms' benefits from the M&A deal. These insiders sell an average less worth of shares amounting to $223,523 and $570,957 in the month after the bid announcement, if their competitors and customers, respectively, have become takeover targets. The treatment effect is stronger when the target firm is producing homogeneous products and has many suppliers. These transactions are systematically highly profitable, implying that insiders incorporate more information into their firms' stock prices, and that the aggregate market suffers from the limited attention constraint. Our results suggest that insiders from these non-focal firms trade on the temporary mispricing of their firms to maximize their personal gains.

To understand the informational contents behind these informed insider transactions, we focus on *operating efficiency hypothesis* and *purchasing efficiency hypothesis*, two non-mutually exclusive and commonly accepted sources of gain in M&A deals. The former suggests that if insiders sell less (more) shares, their firms will perform better (poorer). We use future changes in return on asset, sales growth, and earnings surprises to proxy for future performance. We find strong evidence to support the operating efficiency hypothesis. The purchasing efficiency hypothesis predicts that the takeover bid will lower the price of the merged firms' input materials and the purchasing efficiency will be enjoyed by their competitors and suppliers - the former can enjoy lower input price and the latter can possibly lower the price of their input resources due to the larger downstream demand. Our results, using changes in the cost of goods sold to measure input costs, support this hypothesis.

Additionally, we examine two non-mutually signaling hypotheses – Eckbo's (1983) *industry growth hypothesis*, and Song and Walking's (2000) *higher acquisition probability*. The former implies that the merging firms will reveal innovation that allows rivals to similarly replicate. We employ the unit cost of developing a patent and show that insider transactions can predict the lower cost of developing a patent when their competitor became a target. The signaling higher acquisition probability hypothesis conjectures that markets infer from the deal that the industry is undervalued, or the deal will reveal innovations that allow rivals to similarly replicate efficiency and may engage in future M&A deals of their own. We find a positive relationship between post-bid insiders purchases and their firm becoming a future target.

We rule out the possibility that insiders are trading on their own firm's private information than their better understanding of the M&A deal. We expect insiders' trading activity to vary with the firm-specific price informativeness and if there is intra-board link with the target firm if they simply trade on their private information channel. To proxy for the firm-level informativeness, we follow Tucker and Zarowin (2006) and construct the future earnings response coefficient, and Piotroski and Roulstone (2004) to calculate the return synchronicity. Our results do not vary with the firm-level informativeness and intra-board linkage. Moreover, we find that the cumulative abnormal return of the target firm around the M&A announcement date can predict the insider trading activity. However, the predictability is not seen in the abnormal return of their own firms, suggesting that the main information source of their trading profitability is their better understanding of their economically linked firms' M&A bid.

One main concern in the insider trading literature is endogeneity, as the true motivations behind insider transactions, including private information, portfolio diversification, and personal liquidity needs, are not directly observable, leading to random post-transaction returns, and inconsistent estimates. To mitigate this potential bias, we specify a difference-in-difference regression based on a matched sample firm to isolate the M&A announcement effect within months (-12, 2). We match our treated firms with a group of control firms that were also target firms over months (-12, 12), but without any commercial links to our test firms, on the last six-month returns, book-to-market, and the logarithm of market capitalization at the end of month -1 using the shortest Mahalanobis distance. We also employ a two-stage least square (2SLS) estimator with the mutual fund hypothetical sales proposed by Edmans, Goldstein, and Jiang (2012) and Dessaint et al. (2019) as an instrumental variable (IV) to consider the possible reverse causality that the M&A deal is induced by changes in the treated firm's fundamentals. We conduct placebo tests to show that our results cannot be replicated in a sample of incomplete deal and 1000 randomly selected samples.

Our paper contributes to the extensive insider trading, supply chain, and M&A literatures. The former has predominately argued that insiders generate abnormal profits because they have superior access to their firms' future fundaments. Alldredge and Cicero (2015) show that insiders have better understanding of the public information about their customer firms than the aggregate market. They find the insiders of firms that report at least one major customer systematically generate higher abnormal returns and exploit the limited attention constraint to maximize their personal gains. Ben-David, Birru and Rossi (2019) find that insiders have superior understanding about their industry environment and trade the shares of their industry peer firms in their personal portfolios to generate abnormal returns. However, both these studies are general examinations on the insider trading profitability without conditioning on any specific corporate event or public information announcement and do not test for endogeneity to assess whether insiders are trading on the private or public information. We build on Alldredge and Cicero (2015) to better identify insider trading profitability by focusing on M&A announcements of their economically linked firms. We assess insiders' ability to filter public information, obtain an informational advantage, and conduct informed trading that is not based directly on insider information of their own firms[8]. We eliminate the endogeneity bias by showing that insiders' ability to better understand the public information exists for their customers, but also their competitors.

The existing M&A literature mostly focuses on insider trading either in acquiring or target firms (Agrawal and Nasser, 2012; Fidrmuc and Xia, 2022; Davis *et al.* 2022). As far as we are aware, we are the first to focus on insider trading activity in a firm that is not directly involved in the M&A deal. We use M&A announcement of competitors and supply chain firms, a public information with no potential litigation risk, to assess whether insiders trade on changes in the operating activity of their firm and the increase in its probability of being taken over, and whether they have an advantage in filtering this public information with the help of their private information about their firm's fundamentals. We show that they significantly alter their trading activity following M&A announcements of the competing and supply chain firms. They trade on the deals' operating and purchasing efficiencies gains for their personal benefits. Our results complement recent studies that show that insiders trade on public information, including front running large investors (Chabakauri, Fos, and Jiang, 2022) or indirectly through ETFs just before their firm is subject to a takeover bid to cancel their trades (Eglīte et al., 2023).

The remainder of the paper proceeds as follows. In Section II, we review the relevant literature and develop our hypotheses. Section III describes our sample and the constructions of variables, explains the matching algorithm, and specifies our difference-in-difference regression models. Section IV presents the empirical results. Conclusions are in Section V.

[8] Our setting is also similar to Chabakauri, Fos, and Jiang (2022) who find that insiders restrain from selling and/or increase their buy trades before activist interventions go public, they consider to be a non-inside information, to benefit from potential price increases, and to preserve their ownership and defend their private benefits of control.

II. Literature review and hypotheses development

A bourgeoning strand of insider trading research has focused on the information flows around M&A events and investigated how corporate insiders trade the shares in their companies in response to the M&A announcement. Agrawal and Nasser (2012) show that corporate insiders from the target firms adopt passive trading strategies by systematically selling less prior to the M&A announcement because of the high litigation risk associated with illegal insider trading. Corporate insiders in the target firm commonly adopt the passive trading strategy in one-year prior to the M&A rumor (Davis *et al*., 2022), and before the signing of confidentiality agreements in M&A negotiations (Fidrmuc and Xia, 2022). Chen *et al.* (2022) show that the litigation risk of illegal insider trading is high for acquiring firms and their insiders also adopt passive trading strategies. While the existing literature predominantly focuses on insider trading in acquirer or target firms, we are not aware of any study on insider trading based on their firms' economically linked companies' bid announcements.

We expect corporate insiders to trade profitably in their own firms' stocks when their economically linked firms become M&A targets because their firms will be mispriced as the financial markets are unable to efficiently incorporate their economically linked companies' information into their firms stock prices[9]. This phenomenon, referred to as the limited market attention, arises when investors fail to obtain value-relevant information with limited frequency and accuracy because of the high information acquisition costs (Huang and Liu, 2007). The limited accuracy will directly lead to a cross-section return predictability embedded in the supply-chain information because aggregate investors cannot immediately incorporate all the public announcements of customer firms into supplier firms' stock prices (Cohen and Frazzini, 2008). Hong *et al.* (2007) and Lee *et al.* (2019) observe that aggregate investors are limited in their abilities to understand the full impact of complicated public information due to their specialization and market segmentation. Consequently, value-relevant public information diffuses slowly in financial markets, leading to a return drift.

Previous studies suggest that informed investors actively exploit the limited market attention profitably. Huang and Kale (2013) find that mutual fund managers are more attentive to the public announcement of firms in related industries, better understand the impact of the

[9] Insiders trade also profitably in their own companies' shares when their firms are undervalued by outside investors (Lakonishok and Lee, 2001; Wu, 2019), prior to the release of quarterly earnings announcement (Ali and Hirshleifer, 2017), when the stock prices hit the 52-week high (Lasfer and Ye, 2023), when there is a worsening in the firm-specific or industry level information environment (Wang, 2019; Contreras and Marcet, 2021), and if they narrowly miss their performance-based bonuses (Gao, 2019).

announcement on their peers than outside investors. They actively exploit misevaluations due to outside investors' limited attention through the supply-chain information. Alldredge and Cicero (2015) find that corporate insiders from firms that report at least one principal customer pay attention to their customers' announcements because their sell trades are more loss-averting than their counterparts that did not report any principal customer. Ben-David *et al.,* (2019) show that corporate insiders use their superior knowledge in their industries to trade profitably the shares of their industry peers. Inspired by these findings, we hypothesize that IT firms will be mispriced when their economically linked firms become targets in M&A deals because of limited market attention and their insiders will trade on this mispricing profitably, as they better understand the implication of such public announcement on their own firm.

Cohen and Frazzini (2008) show that the initial market adjustment to the IT firm stock prices is at the correct direction on average but insufficient, leading to up to twelve months price drift. Similarly, Fee and Thomas (2004), Shenoy (2012) and Davis et al. (2021) find that the initial market adjustment to the IT firms' stock prices will correctly imply the impact of the M&A deal on it for long term operational changes. Since corporate insiders are informed investors who have superior access to their firms' future cash flow and operational changes, we hypothesize that they will trade in the same direction as the initial market reaction proxied by the cumulative abnormal returns (CARs), but also on their firms' future performance, as predicted by the *productive efficiency hypothesis* and the *purchasing efficiency hypothesis.* Fee and Thomas (2004) focus on the CARs of corporate customer, suppliers, and rivals of the firms that initiate horizontal mergers to find that merging firms improve their productive efficiency (operating, marketing, or distribution efficiencies), but not their purchasing efficiency (efficiency gains driven by larger demand for input resources that are passed to rivals and customers to benefit the relevant and the downstream industries). These efficiency gains benefit their competitors, suppliers as well as their customers (Shenoy, 2012). Other studies focus on *acquisition probability hypothesis* as a complement to the *productive efficiency hypothesis* to find that M&As will positively impact the target firm's industry if the deal reveals innovations that would allow competitors to replicate these efficiency gains, but only when required[11]. However, because of efficiency-spillover effects after M&A deals, competitors may need to be acquired to replicate the efficiency gain (Gaur, Malhotra and Zhu, 2013; Akhigbe, et al, 2000).

[11] See, for example, Akhigbe, Borde and Whyte (2000), Becher, Mulherin and Walkling (2012), Cai, Song and Walkling (2011) and Davis et al. (2021) and Song and Walkling (2000).

III. Sample and Variable Construction

We first collect a list of US domestic M&A deals with public US target firms from 2003 to 2020, from the SDC Platinum Mergers and Acquisitions database. We exclude exchange offers, repurchases, spin-off, minority stake purchase, recapitalization, acquisitions of remaining interest, privatization, restructuring, reverse takeover, acquisition of certain assets and buybacks deals to be consistent with the previous M&A literature (Suk and Wang, 2021). To ensure that the economic impact of the acquisition is nontrivial, we exclude deals with values of less than \$1 million, where the acquiror already held more than 50% of the target companies' shares prior to the announcement, and when the acquiror did not seek to own more than 50% of the target shares after the deal. We also exclude deals for the same target firm announced within 730 calendar days to ensure a clear treatment effect. This screening resulted in 4,388 M&A deals.

We collect the supply-chain and competitor network data from FactSet Revere[12], a specialized dataset that describes around 1 million vertical and horizontal relationships of large and mostly listed US and foreign firms between 2003 and 2020. FactSet uses its proprietary research method to collect these relationships annually through companies' 10-K fillings, investor presentations, websites, news reports and press releases. The coverage on the supply-chain relationship is much broader than Bloomberg and Compustat Customer file used in Alldredge and Cicero (2015). We compare FactSet with Compustat Customer file which solely records the principal customer disclosed on the firms' 10-K filling and find that FactSet includes around 97% of the customer relationship reported by Compustat. We complete the FactSet dataset by including the remaining 3% links from Compustat to make our dataset coverage noticeably broader than Compustat Customer File, the common source for identifying customer and supplier relationships (Fee and Thomas, 2004; Alldredge and Cicero, 2015).

Each FactSet relationship has a start date, an end date, relationship type and the identifiers of the source and target firms. FactSet reports thirteen different types of relationships, and we follow Boehm and Sonntag (2022) to classify these relationships into three main categories, competitor, customer, and supplier. A target firm is a supplier if it is the source company's manufacturing, distribution, marketing, in-licensing, product licensing, and/or technology partner. It is a customer if it is the source company's out-licensing partner. We

[12] FactSet Revere is available on WRDS. Boehm and Sonntag (2022) and Ding *et al.* (2021) provide a detailed discussion on its coverage and structure.

discard the relationship type of equity investment, investor, joint venture, integrated product offering, and/or research collaboration. We further annualize the relationship data: when the distance between the start date and end date is longer than one calendar day, we recognize these two firms are linked in the year. We combine the relationship dataset with our SDC deal list using *cusip* code and keep the 1,266 deals in which the target firm has at least one linked firm in the year of the M&A announcement. We refer to the target firm in the M&A deal as the economically linked firm, being a competitor, supplier, and/or a customer to the IT firm, as portrayed in Figure 1. We exclude deals in the IT firm, bids where IT firm is linked to the acquiror, cases where more than one linked firm becomes a target firm in the same year, and uncompleted deals. These restrictions reduced our sample to 955 M&A deals.

We compiled all insider transactions in our IT firms from Thomson Insider Filling (TR). We keep all insider open market transactions in Form 4 and exclude problematic trades with cleanse code A or S, and with less than 100 shares, transactions for non-common shares, in line with insider trading literature (Lakonishok and Lee, 2001; Cohen *et al.*, 2012), and any pre-scheduled trades, known as 10b5-1 trades, because the information content embedded is likely to be trivial[13]. We only keep the transactions submitted by the CEO, CFO, COO, chairman of the board and president because these top managers have the best access to the most price-sensitive private information, and they actively trade on it for personal gains (Cohen *et al.* 2012; Cziraki *et al.* 2021). Additionally, we follow Cohen *et al.* (2012) to identify "routine" traders, insiders who have been trading in the same calendar month, in the same direction in the past three calendar years. We identified at the beginning of each year these trades and exclude them as they are more likely for personal liquidity need. We collect analyst coverage data from I/B/E/S, institutional ownership from Thomson Reuters Institutional Holdings File, financial data from CRSP and accounting data from Compustat, focusing only on common shares with the share class code of 10 or 11.

We report the screening details in Appendix 1 Panel A. Our final sample consists of 685 M&A deals undertaken by 559 distinct acquirors for 681 distinct targets with 1,413 distinct IT firms and 2,669 distinct insiders who trade at least once in the months (-12, 2). Appendix 1 Panel B and C show the annual and industry distribution of our sample. There is a clear upward trend in the M&A sample included in the study because FactSet keeps improving its coverage on large US firms. More than 50% of the M&A sample occurred after 2015. We include 75

[13] Rule 10b5-1 adopted by SEC in 2002 allows insiders to set up planned pre-announced trades to protect them against illegal insider trading claims, but Larcker et al. (2021) and Fich et al. (2023) report its opportunistic use.

deals in 2017 and only 12 in 2003. The industry distributions of IT and target firms linked as competitors are similar because firms in the same industry are more likely to be competing. The industry "Machinery and Business Equipment" accounts for the second most of the IT firm samples under all three types of relationship. The distribution of IT firms in the Fama-French 17 industry is overall consistent with Alldredge and Cicero (2015).

Agrawal and Nasser (2012), Suk and Wang (2021) and Fidrmuc and Xia (2022) show that insiders from the target firm in an M&A deal adopt a passive trading strategy - they sell much less than they did one year before the deal announcement because of the high litigation risk involved with actively trading prior to M&A announcement. To control for this possible trading strategy, we aggregate our insider trades at the insider-firm-month level and compute the net purchasing value (NPV) as the dollar value purchase transaction minus sell transaction over the total dollar value to measure insider trading direction (Lakonishok and Lee, 2001). An insider *i* is net buying (selling) in his firm *j* in each month *m* if *NPV* is greater (less) than 0.

$$\mathrm{NPV}_{\mathrm{i,j,m}} = \frac{\$\mathrm{purchase}_{i,j,m} - \$\mathrm{sell}_{i,j,m}}{\$\mathrm{purchase}_{i,j,m} + \$\mathrm{sell}_{i,j,m}}$$

Our main empirical analysis is to investigate whether insider's transactions in IT firm *j* following an M&A announcement of its linked firms is profitable, as proxied by the following buy-and-hold abnormal return (BHAR) for holding period *t*:

$$BHAR_{i,j,m} = \prod_{k=1}^{30}(1 + return_{j,t+k}) - \prod_{k=1}^{30}(1 + mkt_{t+k})$$

where $return_{t+k}$ is the log raw return generated by the IT firm *j* over the holding period t+k and mkt_{t+k} is the corresponding benchmark return. We measure BHAR from one day after the transaction date to the next 30-calendar days, in line with Cohen and Frazzini (2008), Cohen *et al.* (2012) and Alldredge and Cicero (2015), because the stock mis-valuation through the supply-chain caused by limited attention of uninformed investors is mainly in the short term. We first use the CRSP value-weighted market index return to adjust the holding period return, denoted as $\mathrm{BHAR\_m\_30}_{\mathrm{i,d}}$, and then the appropriate size decile portfolio of firms based on NYSE size breakpoints (Alldredge and Cicero, 2015) to control for the unobservable market-related risk that affects all firms with similar size during the same 30-day holding period, to compute $\mathrm{BHAR\_ff\_30}_{\mathrm{i,d}}$. Appendix 2 presents the constructions of all our variables.

We specify a diff-in-diff regression based on a matched sample following Cziraki *et al.* (2021). We match each IT firm with a single control firm in the same month, to minimize the biasedness, using the shortest Mahalanobis distance on the cumulative return in the last six months, the logarithm of the total asset and the book-to-market ratio at the month *t-1.* We restrict that the control firm is not linked to the same linked firm in FactSet and is not a target in a takeover bid in the last and next 12 calendar months. We specify our baseline diff-in-diff regression as follows:

$$NPV_{i,j,m} = \alpha + \beta_1 Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post\times Treat_{i,t} + controls + \tau + \gamma + \rho + u_i$$

where τ, γ and ρ are firm, insider, and month-year fixed effect[14], respectively. We cluster our standard errors at the firm-month level as Alldredge and Blank (2019) show that insiders cluster their trades with their colleagues. The main independent variables include treatment dummy $treat_i$ that equals to one for firms that have their linked firms become the target, the post-treatment period dummy $post_t$ that equals one for month (0,2) with month 0 as the M&A announcement month, and their interaction $treat \times post_t$. We focus on three months from 0 to 2 months post-M&A announcements because the stock misevaluation caused by the market attention constraint is mainly a short-term phenomenon (Cohen and Frazzini, 2008). We use samples in month (-12, 2) to estimate the baseline diff-in-diff regression. If there is a systematic increase (decrease) in the insider transactions after the M&A announcement, β_3 should be positive (negative) and statistically significant.

We control for size ($Ln(makt\_cap)_{j,m}$), momentum ($mom_{j,m,(d-1,d-365)}$), book-to-market ($bm_{j,m-1}$), institutional ownership ($insti\_hold_{j,q}$), Herfindahl index based on the number of institutional investors ($insti\_HI_{j,q}$), Amihud (2002) illiquidity measure ($illiq_{j,m-1}$), sell-side analyst coverage ($numest_{j,t-1}$), return on asset ($roa_{j,t-1}$), research and development cost ($rd_{j,t-1}$), leverage ($lever_{j,t-1}$), total normalized trading volume ($vol_{j,(-90,-1)}$), standard deviation of stock returns ($sd_{j,(-365,-1)}$), and change in standard deviation ($delta\_sd_{j,(m-3,m-1)}$). We proxy the age of insiders as the time distance between their first occurrence in TR and the insider trading day. We proxy the tenure using the distance between their first occurrence in the same firm and the insider trading day. We also include dummy variables of one if the acquiror is a competitor, customer or supplier, of the target firm, respectively, and zero otherwise.

[14] We find similar results when we replicate all diff-in-diff regressions with firm, insider, and year fixed effects.

IV. Empirical Results

A. Univariate Evidence

We present the descriptive statistics in Table 2. In Panel A, we report the monthly average of all variables included in the regression for these three types of relationships separately. The average total asset is $17.5 billion, $14.6 billion, and $53 billion for the IT firm where the competitor, customer, and supplier, is subject to a takeover bid, respectively. IT firms that have their suppliers become the target are larger than other IT firms because firms with major suppliers are more likely to be in the asset-intense industry and produce at a larger scale and expected to have more assets. In contrast, the differences between their market capitalizations are relatively smaller. IT firms that have their competitor, customer or supplier becomes the target are on average worth $14.2 billion, $16.6 billion, and $26.0 billion, respectively. The relatively smaller difference in market capitalization is also reflected in their similar book-to-market value of 0.416 for competitors, 0.424 for customers, but smaller than the 0.47 for suppliers. The suppliers of IT firms have also a relatively larger sell-side analysts' followers, but insiders' age and tenure are relatively similar across the three relationships.

We find at least one competitor relationship between IT and target firms in 457 deals, customer relationship in 287 deals and supplier relationships in 318 deals. There are 1,106 competitor relationships, and only 305 out of 1,106 have IT and target firms in the same four-digit SIC industry. The literature used the four-digit SIC industry as a primary way to identify competitors (Fee and Thomas, 2004; Davis *et al.*, 2021), but FactSet's proprietary research method enables us to identify a larger number of competitor relationships between firms in different industries[15]. More than 80% of these M&A deals are diversification deals, where the acquiror is unrelated to the target in the FactSet dataset mainly because of our restriction that the IT firm is unlinked to the acquiror. If the acquiror is linked to the target, the likelihood that the acquiror is also linked to the IT firm is high. The average market value of the customer target firm is $4.4 billion, and the average deal value of the customer target firm is $6 billion, are both the largest among these three relationships because major customers are larger firms that produce at a larger scale. However, the average bid premium of these three types is similar, ranging from 34% to 37%. We also report the insider trading activity measured between month

[15] It is far from reality that firms only compete with peers in the same four-digit SIC industry. For instance, Amazon (gvkey: 064768) which has primary SIC code 5961(Catalog and Mail-Order Houses) is competing with Oracle (gvkey: 012142) which is in SIC industry 7372 (Pre-packaged Software) over their cloud computing and storage services since 2016. Also, Compustat Segment file would not correctly identify the competitor relationship. FactSet identifies the competitor relationship, but the conventional four-digit SIC code method does not. The competitor relationship has been reported by Oracle on its website https://www.oracle.com/cloud/oci-vs-aws/.

(-6, -1). The average NPV for all three types is negative and ranges from -0.50 for the competitor to -0.63 for the customers. The negative NPVs are consistent with the insider trading literature because compensation committees frequently reward insiders with free shares (options) to align their interests with the shareholders' (Lakonishok and Lee, 2001).

In Panel B, we report the CAR for the M&A announcement effect for all acquiror, target and IT firms. Notably, we compute and report the CARs for IT firms even if they do not report any insider transactions in our focus period. We report three different event windows that are around day (-30,-2), (-1,1) and (2,30) for all three relationships. The CARs $_{-1,1}$ are 27.1%, 25.5% and 25.9% when the target firm is a competitor, customer, and a supplier, respectively. The respective acquiring firms' CARs are -1.1%, -1.3% and -1.5%, in line with previous M&A empirical literature. IT firms generate significantly smaller excess returns of 0.7% and 0.2% for competitor and customers, respectively. over the event periods, providing an opportunity for insiders to time the market as they have a better understanding of the impact of the M&A deal on their companies, in line with Cohen and Frazzini (2008) and Alldredge and Cicero (2015) who show that the limited attention of outside investors leads to an insufficient price adjustment, leading insiders to trade on the public announcement for personal gains. More importantly, the CARs $_{-1,1}$ for competitor and customer are both positive and zero for suppliers, and we expect insiders will increase their holdings, but not for suppliers in line with H_3.

[Insert Table 2 here]

In Table 3, we provide a comparative analysis of treated and control IT firms. Panel A reports the summary statistics during the pre-treated period to validate our matching procedure. The results show that the differences in the aggregate insider trading pressure calculated for the corresponding period at the beginning of month 0, $Sum\_NPV_{(-6,-1)}$ and $Sum\_NPV_{(-12,-1)}$, are not statistically significant, highlighting the appropriateness of our matching algorithm, even though we do not match on these two variables. These results suggest also that insiders are not trading on upcoming M&As before their public announcements. Similarly, our treated and matched firms have similar book-to-market ratios, $bm_{j,m-1}$, and 6-month return, $ret6_{j,m,(d-1,d-180)}$, but our treated firms are marginally larger than the matched firms competitors and suppliers. To better understand the impact of the difference, we investigate the scale of the difference in market capitalization between treated and control firms. We find that the difference for competitor relationship is on average 7.7% and 17.8% of the standard deviation computed using all CRSP firms in the month -1 for competitor and supplier, respectively. Furthermore, if we divide all firms into deciles according to their market capitalization at the end of month -1, all pairs of treated and control firms are in the same size decile and the difference is on average 43% and 72% of the standard deviation computed in the size decile for competitor and supplier, respectively. These two differences are statistically significant but economically small, and therefore we recognize that our matching algorithm remains appropriate. Other variables not used in the matching algorithm remain mostly insignificant.

In Panel B, we focus on the difference between treated and control firms in the post-announcement period. Insiders in the treated firms systematically sell less shares than control firms for competitor and customer relationships but not for supplier relationship. Their trades are also more profitable than their counterparts' from the control firms. Their purchase transactions generate higher abnormal returns for customer and supplier relationships. In contrast, their sell transactions yield lower abnormal returns which is a gain for sell transactions for competitor and customer relationships. The increase in the return predictability remains significant when the abnormal return is measured by $BHAR\_m\_30_{i,d}$. The univariate evidence is consistent with Alldredge and Cicero (2015) which reports that insiders sell transactions are more loss averting when their firms report major customers.

[Insert Table 3 here]

We further conduct a formal parallel trend assumption test following Angrist and Pischke (2009), Cengiz *et al.* (2019) and Aktas *et al.*(2021). We define variable Pre_m ($Post_m$) equal to 1 for treated firms in month *m* before (after) the M&A announcement month 0, and zero otherwise. We use the same set of control variables as in our baseline diff-in-diff regression and present the result in Appendix 3. The coefficients of Pre_m are mostly statistically insignificant for all three relationships and for all three different dependent variables, meaning the trend in month (-12, -1) between control and treated firm is parallel after controlling for firm characteristics that can explain insider trading activity and profitability. The regression output alleviates the concern that the post-announcement results are driven by the matching algorithm's inappropriateness to obtain the control group and the use of the diff-in-diff estimator.

B. Insider trading activity around the M&A announcement

We report the regression output for our baseline diff-in-diff regression in Table 4 and only report the coefficients of a selected range of control variables for brevity. We estimate the regression for competitor, customer, and supplier separately and report regression results in column (1), (3) and (5), respectively. The coefficients of $(\text{Post}\times\text{Treat})_{I,t}$ are 0.044 and 0.062 for competitor and customer, respectively, both statistically significant at the 95% confidence level. The coefficient is statistically indifferent from zero for the supplier. If an IT firm's competitor or customer has become the target in an M&A deal, the expected net purchase ratio will increase by 4.4% and 6.2% for competitor and customer, respectively. If we use the average insider trading value between month (0, 2) to compute the economic impact, insiders will buy an additional \$223,523 and \$570,957 worth of shares for the competitor and customer relationship, respectively. These results support our hypothesis H_1 that the M&A announcements for their competitor and supplier systematically motivate insiders to increase their holdings by selling less. The higher net purchase ratio implies that the outside investors fail to incorporate all the information of the M&A deal through the supply chain. Moreover, these results support H_3 that insiders will trade in the direction with the initial market reaction proxied by CAR, further highlighting that the market reaction to M&A announcement is reckoned by the insiders as insufficient. Therefore, these IT firms remain mispriced even two months after the announcement month. Insiders from IT firms see their firms are undervalued, and the full impact of the M&A deal has not been incorporated into their stock prices. Consequently, they keep their positions for a longer period to generate a higher abnormal return for personal gain.

The coefficients of $\text{Ln(makt\_cap)}_{j,m}$ and $\text{mom}_{j,m.(d-1,d-365)}$ are all negative and significant across all three types relationships, suggesting that insiders are more likely to sell their shares when their firm's is large and its stock returns are high, in line with previous literature that documents that these two factors are the major determinants of insider trading activity (Lakonishok and Lee, 2001; Cohen *et al.*, 2012). The coefficients of institutional holding $\text{insti\_hold}_{j,q}$ and the Herfindahl index $\text{insti\_HI}_{j,q}$ are mostly insignificantly, highlighting that the trading decision of insiders is not affected by the presence of institutional investors. The results suggest that the informational content embedded in corporate insider trading is complementary to that obtained by other informed investors, such as mutual fund managers, consistent with the finding that insiders generally trade on different informational contents with other informed investors (Wang, 2019).

We further remove IT firms with many linked firms because losing one of them is unlikely to substantially impact the business prospects. The exclusion of these treated firms should not weaken our results, and this refined sample will serve as a robustness test for the regression. In each month, we divide all IT firms of each relationship type into quintiles in accordance with the number of linked firms. We remove the top quintile and their corresponding control firms from the sample and re-estimate these baseline regressions. We report the results in columns (2), (4) and (6). The coefficients of $(Post \times Treat)_{i,t}$ remain positive and statistically significant at the 95% confidence level for competitor and customer, but still insignificant for the supplier, implying that our previous results are robust to the exclusion. Overall, these results support our hypothesis that insiders trade profitably on the M&A announcement of their economically linked firms.

[Insert Table 4 here]

C. Target firm heterogeneity

In this section, we further explore the target firm heterogeneity. Although we cannot directly support the productive efficiency and purchasing efficiency hypotheses, the heterogeneity analysis will shed additional light on the plausibility of these two hypotheses. We first focus on the specificity of the target firms. We assume that if they produce homogeneous products, then insiders from IT firms are likely to sell less with greater intensity because it is easier for merging firm to obtain the purchasing efficiency as the demand for the input resource of homogeneous product is larger. Consequently, the purchasing efficiency is easier to be passed onto their competitors and customers, but the effect is unclear for their suppliers as suggested in Table 1.

We follow Barrot and Sauvagnat (2016) and use two proxies to identify target firms that produce homogeneous products. We first borrow the industry classification from Rauch (1999)[16] who classifies 1,189 four-digit SITC Rev.2 system industry codes into homogeneous and differentiated product industry. The classification scheme recognizes that products sold on an organized exchange or are reference priced are more likely to be homogeneous products, and other products are differentiated products. We use Feenstra (1996)[17] to link the SITC code with SIC code, and code industry that is on an organized exchange as 0, in the reference priced industry as 1 and producing differentiated product as 2. Since one SITC code can correspond to several SIC code, we compute the average for a SIC code, and classify a SIC industry is producing homogeneous product if it lies below the median along this dimension (Barrot and Sauvagnat, 2016). We create a dummy variable $homo_{i,j}$ equal to one for firms in the

[16]We thank Professor Rauch to make the data public https://econweb.ucsd.edu/~jrauch/rauch_classification.html
[17]We thank Professor Feenstra to make the data public https://cid.econ.ucdavis.edu/usix.html

homogeneous product industry and zero otherwise. For the second measure, we employ the number of patent that a firm receives to proxy its specificity. We hypothesize that firms that receive more patents are specialized. We collect the number of patents from USPTO, and use the link table provided by Arora, Belenzon and Sheer (2021) to match the firm with their patents granted prior to 2015. For those granted after 2015, we manually match the name, state and city of assignees using fuzzy matching algorithm. We further consider firms in the top quintile portfolio formed according to the number of patents granted in a year to be innovative, and assigned a dummy $innov_{i,j}$ equal to one and zero otherwise.

We employ these two moderators in the diff-in-diff regression and report the regression in Table 5 Panel A and B. We control for all the main levels of interaction variables and omit their outputs for brevity. Panel A shows that insiders will significantly reduce their selling with greater intensity when the target firm is producing homogeneous products for competitor and supplier relationships. The results are similar in Panel B, where we proxy differentiated product producer using the number of patents. Insiders reduce their selling with lower intensity when the target firm is innovative firm for competitor and supplier relationship. These results support the purchasing efficiency hypothesis that the merging firm can increase their purchasing power to lower the input price, and the efficiency gain will be shared with their industry peers and customer firms. The result is insignificant for customer relationship because the overall effect on the IT firm is not significant. The lower input price is a negative news for IT firms, but the merging firm will have a larger demand, and consequently, the net effect is zero for IT firms.

In Panel C, we create dummy variables for target firm that is in the top quintile of firms with the most competitor and employ the dummy variable as the moderator variable. The results show that insiders from IT firms are more likely to reduce their selling when their supplier firms have many competitors for all three relationships because the coefficient of $\text{Post}\times\text{Treat}^{*}\text{top}_{i,j}$ is positive and statistically significant. These results are mostly consistent with our previous hypothesis that the purchasing efficiency will be gained for a merging firm in a large industry with many peer firms. Moreover, insiders are also reacting with greater intensity if their customers have many competitors, in line with both the productive efficiency and the purchasing efficiency as insiders recognize the increase in the efficiency for customer firms in a more competitive environment should be higher to gain comparative advantage, further boosting IT firms' turnover.

We use the number of suppliers to measure the complexity of the supply chain for the target firms. If the target firm has a large supply chain, the limited attention constraint should play a more significant role because it is more difficult for the market to understand the impact of the deal on all firms on the chain. Therefore, insiders from IT firms will have a larger informational advantage and should trade with greater intensity. The results in Panel D confirm our hypothesis. The coefficient of Post×Treat*top$_{i,j}$ is positive and statistically significant for customer, and negative for competitor and supplier, meaning insiders will react to the M&A announcement with different intensity depending on the target firm supply chain complexity. The negative coefficient for competitor relationship is possibly attributed to the various differentiated input resources that the target firm require to produce their final products. There will be no significant decrease in the input price when competitors have many suppliers, and therefore, insiders from IT firms recognize they cannot replicate the efficiency gain and will have comparative disadvantage. However, insiders react positively to the announcement of their customers with many suppliers. The results support our findings that the net effect for suppliers is positive because the increase in demand outweighs the drop in price, and other competitors of the merging firm are unable to gain the same purchasing efficiency.

In Panel E, we sort firms in accordance with the number of customers they report, a proxy for their market shares, to find that insiders reduce their sell trades with greater intensity in such target competitors. The results indicate that insiders from IT firms expect the merging firm with many customers to gain both purchasing efficiency and productive efficiency, and these efficiency gains will be passed onto their customers and competitors. Moreover, insiders from IT firm that is the supplier of the merging firm will also reduce selling with larger intensity, because the net effect for these suppliers is positive and the larger demand exceed the downward pressure on the output price.

In Panel F, we focus on the bid premium and create dummy variable equal to one for the top quintile of deals with the highest bid premium. We find that insiders systematically sell more when their competitors or customers have been offered a very high bid premium. Although we cannot infer insiders' motivation directly from these results, these insiders recognize that these high premium deals are value-destroying for the IT firms, and they are less likely to receive efficiency gains from these deals. The results are consistent with Malmendier and Tate (2008) who show that overconfident CEOs are more likely to initiate value-destroying deals and overpay bid premium. In Panel G, we focus on the percentage of consideration paid in stocks and show that insiders react more positively when their competitors are bought largely using acquiror's stock, in line with Di Giuli (2013) and Eckbo, Makaew and Thorburn (2018) who argue that more informed target managers use a larger fraction of stock financing. Target managers believe the deal is value-creation and will generate long-term positive effect on the merging firm, and therefore are willing to accept a high percentage of stock consideration. Consequently, insiders from IT firms will consider the percentage of stock financing as a signal and to trade the shares of their own firms accordingly. We do not find similarly evidence for customer and suppliers relationships. In unreported results, we further explore the impact of tender offer deals, the industry relativeness between acquiror and target defined by their first three-digit SIC codes, the relative size ratio between acquiror and target, and the deal attitude. We do not find significant results and thus omit these outputs.

[Insert Table 5 here]

D. Insider trading profitability around the M&A announcement

Previous results have indicated that insiders will adopt a passive trading strategy by systematically selling less when either their competitors or customers have become the target in a M&A deal, and they will not significantly alter their trading activities if their suppliers have become the target. In addition, they may better time their transactions by selling (buying) more when their firms have become overpriced (underpriced). Their post-transaction returns will allow us to investigate the informativeness embedded in their transactions and to study whether they have better understanding of the impact of the deal on their own firms than outside investors. Alldredge and Cicero (2015) show that insiders from firms that report principal customers earn a higher abnormal return than their peers from firms that do not have principal customers without conditioning on any specific corporate event. The specific M&A setting allows us to extend their findings to the other two relation types to investigate whether insiders truly have better understanding of the public announcement than outsiders.

In Table 6, we use the $BHAR\_m\_30_{i,d}$ and $BHAR\_ff\_30_{i,d}$ as our dependent variables, and estimate our diff-in-diff regression. Since we have documented that insiders adopt passive trading strategy, we additionally interact $Post \times Treat_{i,j}$ with $NPV_{i,j}$ to see whether the return predictability is varying with insider net purchasing value, in line with Cziraki *et al.* (2021). We include all the control variables, but omit to report their coefficients for brevity. The coefficient of $Post \times Treat_{i,j}$ is positive and statistically significant for all three relationships regardless the abnormal return measures used, suggesting that insider transactions are systematically profitable after M&A announcements. The coefficients are slightly larger and remaining significant if the dependent variable is $\text{BHAR\_ff\_30}_{i,d}$. These results support our previous findings that insiders on average sell less after the M&A announcement, and their firms yield higher excess returns following the announcement.

The coefficient of $\text{Post}\times\text{Treat}\times\text{NPV}_{i,j}$ is also positive and statistically significant for all three relationships regardless of the profitability measure. The result indicates that when insiders increase holdings, leading to higher NPV, their trades are more profitable. The results further reaffirm the hypothesis H_2 that insiders have better understanding regarding their firm's prospects and they actively trade on it for their personal gains. In unreported results, we remove the top quintile IT firms that have most of linked firms as well as their corresponding control firms from the sample and re-estimate these baseline regressions. The coefficients of $\text{Post}\times\text{Treat}\times\text{NPV}_{i,j}$ remains positive and statistically significant across all three relationships and for both abnormal return measures.

Overall, our results are consistent with Alldredge and Cicero (2015) that insiders have better ability to analyze the impact of public announcement on their firms than outsiders. Furthermore, their better understanding of public information is not only witnessed when IT firms report principal customers, but when IT firms also have competitor or suppliers. Our results also provide support to Cohen and Frazzini (2008) who document outside investors' delay in incorporating public information through supply-chain because of their limited attention. We show that the limited attention will induce stock mispricing which further motivates insiders to trade profitably on the public information.

E. Reverse causality: Two-Stage Least Square Regression

However, our findings may be driven by changes in the business prospects of the IT firms, which may reversely and adversely cause the linked firms to become more vulnerable to acquiror. If acquiror can anticipate the change, they may negotiate a deal with the affected firms in advance. For example, if the IT firm is the major competitor of linked firm and IT firm launches a major product that will substantially lessen the market share of the linked firm, linked firm will be worth less and become cheaper to be acquired. To mitigate this effect, we apply an instrumental variable (IV) approach that exploits the exogeneous shocks that are outside the control of IT firms which may become treated firms in our sample, because they have a higher likelihood of becoming an M&A target. Our instrument builds on Edmans *et al.* (2012), Dessaint *et al.* (2019), and Boehm and Sonntag (2022), who show that when large mutual funds fire-sell a part of their portfolio to fulfil the capital withdrawal request from their investors, the capital outflow will place a downward pressure on the share prices of firms in their portfolio and increase the likelihood of these firms to be acquired. The occurrence of the capital outflow is exogeneous to these firms that have been sold by mutual funds, and thus unrelated to their prospects.

We follow Edmans *et al.* (2012) and Dessaint *et al.* (2019) to construct hypothetical shares sold by large US mutual funds in response to a sudden capital outflow. The shares sold is hypothetical not actual because mutual funds are not required to disclose the reasons behind their investment decisions. Therefore, we can only infer their motivations from their disclosed holdings in different firms' shares. The construction details for the hypothetical shares sales are described in Appendix 4. We further sort all firms into quintiles each year in accordance with the hypothetical number of shares that have been fire-sold by mutual funds, and we recognize firms at the bottom quintile are those experienced an extreme downward pressure on their stock prices. We create dummy variable $MFHSD_{j,t}$ equals to one for firms that are at the bottom quintile, zero otherwise. Agrawal and Nasser (2012) and Boehm and Sonntag (2022) have shown that there is generally a one-year lag between M&A negotiation period and M&A announcement date, and therefore we include observations from month (-24, 2) to reflect the additional one-year lag between outflow event and M&A announcement. Finally, we compute our IV $MFHS_{j,t}$, which is a continuous variable equals to the market capitalization weighted average $MFHSD_{j,t}$ of all linked firms in year *t* for a given relationship type. If control firm does not have any linked firm in a given year, the variable is set to be zero.

The IV is appropriate because it reflects an increase in the probability that a firm will be acquired, and thus can directly predict the probability of a firm becoming a treated IT firm in our setting. Thus, we recognize the IV relevance condition is satisfied, and we conduct formal test on the condition at a later stage. However, the exogeneous shock to the linked firm's stock price is unlikely to have any direct impact on both the linked firm's business operation and IT firm's business environment because the shock is nonfundamental and exogeneous (Dessaint *et al.* 2019), further highlighting the plausibility of the exclusion condition.

Table 7 panel A reports the results with NPV as the dependent variable in the second stage regression. We exclude the control variables for brevity. We use the IV $MFHS_{j,t}$ and the interaction term between the same IV and $PostD_{i,j}$ denoted as $MFHS^{*}PostD_{i,j}$ to jointly predict the endogenous variable $TreatD_{i,j}$, and the interaction term $Post\times Treat_{i,j}$ in two separate first-stage regressions. To better demonstrate the incremental predictive power of our IV on the

$TreatD_{i,j}$, we report the first-stage regression without the interaction term $MFHS^{*}PostD_{i,j}$ in column (1), (3) and (5) for competitor, customer and supplier, respectively. From these results, we can observe that the coefficients of $MFHS_{j,t}$ are all positive and statistically significant at the 99% confidence level for all three relationships. The Kleibergen-Paap *F*-statistic is 41.17, 74.10 and 18.58 for these three relationships, respectively. The first stage F statistics are all above 10, which is the minimum value to alleviate the weak instrument concern, providing significant support for the relevance condition, indicating $MFHS_{j,t}$ is an appropriate IV. If we include the interaction term $MFHS^{*}PostD_{i,j}$, the Kleibergen-Paap *F*-statistic is 19.19, 36.86 and 9.22 for these three relationships, respectively. The coefficient $Post{*}\widehat{TreD}_{i,j}$ of 0.131, 0.203 for competitor, and customer, respectively, are all statistically significant at the 95% confidence level, but insignificant for supplier. In addition, the unreported Anderson-Rubin *F*-statistic rejects the null hypothesis and indicates that the endogenous regressor $TreatD_{i,t}$ is statistically significant at the 95% confidence level for competitor and customer. The Anderson-Rubin F-statistic is robust to the presence of weak instrumental variable (Andrews, Stock and Sun, 2019) and thus reaffirm our previous findings that insiders from IT firms will systematically sell less shares after their competitor or customer firms have become the target in a M&A deal. In unreported result, we also check for a potential weak instrument using the Stock and Yogo (2005) test and the Shea Partial R-squared values, and we find that our IV does not suffer from weak instrument problem throughout the study. The Difference-in-Sargan *C*-statistic rejects the null hypothesis that the $TreatD_{i,t}$ is exogenous to the net purchase value. Since our 2SLS is just-identified as we only have one IV with one endogenous variable, the *Difference-in-Sargan C-test* is equivalent to a *Hausman* test comparing the estimates of 2SLS with fixed effect (FE). The significant *C*-statistics confirm the necessity of applying 2SLS rather than the FE estimator.

In panel B, we change the dependent variable of the second stage regression to $BHAR\_m\_30_{i,d}$. $MFHS_{j,t}$ remains a valid IV despite a decrease in the sample size. The coefficient of $MFHS_{j,t}$ is quantitatively similar to the result in panel A and all Kleibergen-Paap *F*-statistics are well above 10 in the first stage when $MFHS_{j,t}$ is the only IV included. The coefficient of $Post{*}\widehat{TreD}_{i,j}$ is 0.034, 0.054 and 0.040 for competitor, customer and supplier, respectively, and they are all statistically significant at the 90% confidence level. These results are consistent with our previous findings that insiders will better time their transactions after the M&A announcement to generate a higher abnormal return. Overall, our results remain robust when using 2SLS estimator, further emphasizing that our conclusions were not driven by the endogeneity induced by the reverse causality.

[Insert Table 7 here]

F. The source of gain behind informed trading

In this section we assess the source of gain behind these informed insider trading activities. We expect the insider trading activity will predict the IT firm's future efficiency gain attributed to the future M&A deal. To examine the productive efficiency hypothesis, we focus on five measures of future business performance efficiency: (i) change in the return on asset between years 0 and 2; (ii) normalized earnings surprise measured by DellaVigna and Pollet (2009) between quarter 4 and quarter 5; (iii) sales growth between year 0 and year 2; (iv) change in the unit cost of a patent between year 0 and year 3; and (v) change in the cost of goods sold (COGS) between year 0 and year 2. These five items directly reflect the improvement in operating performance predicted by the operating efficiency hypothesis and shown by existing literature to be sensitive to supply-chain changes (Alldredge and Cicero, 2015; Cziraki *et al.*, 2021; Boehm and Sonntag, 2022). We expect the deal announcement to completely and fully exert its impact on the IT firm's balance sheet at least one-calendar year from the announcement year.

We keep the same regression specification as our diff-in-diff regression and interact the $\text{Post}\times\text{Treat}_{i,j}$ with $\text{NPV}_{i,j}$. If insiders are indeed trading on the change in their performance affected by the M&A deal, the coefficient of $\text{Post}\times\text{Treat}\times\text{NPV}_{i,j}$ should be positive and statistically significant. The less (more) insiders sell after the M&A announcement, the better (worse) their firms' future perform. In unreported results, we also conduct a parallel trend assumption test following Angrist and Pischke (2009) and Aktas *et al.* (2021) using these dependent variables to ensure the appropriateness of diff-in-diff regression specification. We confirm that the control and treated samples do not show different pre-trend before the M&A announcement and our diff-in-diff framework is appropriate in the setting.

We report the results for $\Delta\text{roa}_{t,j}$ in Table 8 panel A. The results show that the coefficient of $\text{Post}\times\text{Treat}^{\times}\text{NPV}_{i,j}$ is positive and statistically significant at 90% and 95% for competitor and customer, respectively, but insignificant for supplier, suggesting that when insiders sell less after their linked firm's M&A bid, their firm's return on asset will increase. However, we consider that if an IT firm has many suppliers or customers, losing one of them is unlikely to make a substantial impact on their business performance. We, therefore, divide all IT firms into quintiles each year according to the number of their linked firms, we remove the top quintile IT firms with their corresponding control firms from our sample, and re-estimate the regression. If the source of gain is indeed the M&A announcement of their linked firms, the coefficient should become larger. The results reported in Panel A Column (4) to (6), show that while the coefficient of Post×Treat×$NPV_{i,j}$ remains insignificant for supplier, it becomes more significant and increases from 0.015 to 0.021 for competitor, and it increases from 0.019 to 0.025 for customer, further reaffirming that insiders trad on M&A announcements of their linked firms.

We follow DellaVigna and Pollet (2009) to construct the standardized unexpected earnings ($SUE_{q,j}$) and explain the construction in Appendix 2. We calculate the change in $SUE_{q,j}$ between quarter 4 and quarter 5, and use it as dependent variable in our regression. Table 8 panel B shows that the coefficients of Post×Treat×$NPV_{i,j}$ of 0.025 for competitor, 0.044 for customer, and 0.010 for customer are statistically significant. If we remove firms with many linked firms, the coefficients all become larger and more significant for competitor and customers. These stronger results further support our conclusions that the M&A deal will make an impact on IT firm's business performance, insiders better understand the impact than outsider and systematically trade on it. In panel C, we employ the $\Delta sale_{t,j}$ as our proxy for business performance, and we obtain similar results. Insider transactions after the M&A announcement systematically predict the future growth in sale for both competitor and customer relationships, and the coefficients become larger and more significant if we exclude firms with many competitors and customers. The coefficient is constantly insignificant for supplier. These results support the *operating efficiency hypothesis* that competitors and suppliers of the target firm will see an improvement in their firm performance attributed to the M&A deal.

Moreover, the signaling industry growth hypothesis predicts that competitor firms can replicate the innovation without being acquired by other firms. To investigate this hypothesis, we employ the change in the unit cost of a patent as the dependent variable between year t and t+3. We extend the period to the 3rd year after the M&A deal announcement because we use the patent grant date to match our main dataset and there is an additional one-year lag between the patent application date and patent grant date. We use the research and development cost divided by the number of patents granted in the same year to compute the unit cost of a patent. The results reported in Panel D show that the coefficient of Post×Treat×$NPV_{i,j}$ is negative and statistically significant, implying that a 10% increase in NPV reduces the unit cost for obtaining one more patent by 0.116 million after the M&A deal. The relationship is insignificant for customer and supplier, as IT firms are in the downstream and upstream cannot benefit from the innovation revealed from the deal. These results are robust to the exclusion of top quintile sample and are consistent with the signaling *industry growth hypothesis*.

We investigate the purchasing efficiency using the change in the cost of goods sold (COGS), the most direct measure to gauge the input price, normalized by sale, as a moderator. Table 8, Panel E shows that the coefficient of $Post \times Treat \times NPV_{i,j}$ is negative and statistically significant for competitor and customer relationships, and insignificant for suppliers. These results imply that when insiders are buying more after the M&A announcement, their firms can enjoy the purchasing efficiency because of the larger industry-wise demand attributed to the merging deal of their competitors. Furthermore, a larger merging customer will have a larger demand for their input resource from suppliers, these suppliers can also benefit from the larger demand to lower their input prices, consistent with the *purchasing efficiency hypothesis*.

We further focus on the supplier relationship by excluding the linked firms that have many peers in the same four-digit SIC industry each year, as IT firms can find alternative suppliers easily and thus alleviate the potential impact on their operating performance. In the entire Compustat file, we count the number of firms in a four-digit SIC industry each year and divide all four-digit SIC industries into deciles. We further remove deals in which the linked firms are the top decile each year, as well as removing the corresponding IT and control firms. The results in panel F show the coefficients of $Post \times Treat \times NPV_{i,j}$ of 0.01, 0.04, and -0.074 when the proxy is $\Delta roa_{t,j}$, $\Delta sale_{t,j}$ and $\Delta COGS_{t,j}$, respectively, are all statistically significant. The coefficient becomes insignificant for $SUE_{q,j}$, implying analysts can correctly forecast firms' earnings information when they do not have many alternative suppliers. The insignificant results for the change in the cost of patent further implies that customer firms cannot gain innovation efficiency from the upstream M&A deal. In unreported results, we also remove the top decile for competitor and customer relationships and replicate all results in Table 8. For customer, we find the coefficients of $Post \times Treat \times NPV_{i,j}$ for $\Delta roa_{t,j}$, $\Delta sale_{t,j}$, and $\Delta COGS_{t,j}$ remain robust with the expected sign and insignificant when the dependent variable is $SUE_{q,j}$ and change in cost of a patent. For competitor, the coefficient is only significant with the expected sign when the dependent variable is change in cost of a patent. The coefficient is insignificant for all other proxies. The insignificant result for competitor further highlights that firms are not necessarily competing with their peers in the same four-digit SIC industry and the conventional method to identify competitor is inaccurate. However, the larger and more significant coefficients for customer and supplier justifies that using four-digit SIC code to identify alternative customers and suppliers is reasonable and not easily finding alternative customers or suppliers will have a more substantial effect on IT firms' performance. These results provide support to hypothesis H_4 that insiders from IT firms trade on the change in their firm's future business performance affected by the M&A deal, and support both the *operating efficiency hypothesis* and *purchasing efficiency hypothesis*.

×[Insert Table 8 here]

G. Insider trading and the propensity of future M&A activity

We further assess whether their profitable trades signal an improved prospects of their firm's receiving and initiating takeover bids. Song and Walkling (2000) and Davis *et al.* (2021) show that there is an increasing probability for the competitor of a target firm to be acquired in the next one year because the preceding deal demonstrates an improved industry prospect. We aggregate all the insider trading activities in IT firm *j* between month (0,2) to construct the net purchasing value $NPV_{j,(0,2)}$. Then, we define the dependent dummy variable, $TargetD_j$, equal to one if the IT firm has become the target between month (3,14), and zero otherwise. Similarly, we define $AcquirorD_j$ equal to one when IT firms initiate an M&A deal in months (3,14), and zero otherwise. We include 4,816 major M&A deals collected from SDC. Appendix 1 provides the screening details. We follow David *et al.* (2021) to include a refined set of control variables representative of the various theories of merger gains and management's motives to engage in M&A, including the price run up 30 days from the end of month 0 denoted as $runup_{j,m,(d-30,d-1)}$, the total number of M&A deal announced In the same 4-dig SIC industry in the last 12 months $ind\_activity_{j,(m-1,m-12)}$, and other control variables as described in Appendix 2.

Table 9 shows that $NPV_{j,(0,2)}$ is positively and significantly correlated with receiving a takeover bid in the next twelve months for all three relationships. The result indicates that when insiders from IT firms are selling less after the M&A announcement of their linked firms, IT firms are more likely to receive a takeover bid, allowing them to kept their ownership in their firms to avoid an opportunity loss, since receiving a bid is associated with an increase in the stock price as evident by our previous evidence. We also find that when IT firm's supplier becomes the target, the $NPV_{j,(0,2)}$ is negatively correlated with the probability of IT firm initiating a bid, and the relationship is statistically significant at the 90% confidence level. Initiating a M&A deal usually leads to a decrease in the acquiror's stock price on average, insiders would avoid the opportunity loss by reducing their ownership in the firms in advance. These findings suggest hypothesis H_5 and corroborate with the *signaling hypothesis* that when insiders trade after the M&A announcement of their linked firms, they will consider the further M&A activity of their firms. Other firm-level control variables, omitted for brevity, are all insignificant.

H. Informational channel behind informed insider trading activity.

In this section we assess whether the conventional *private information channel* due to their superior access to the information that outside investors would not know at the time of the M&A announcement, or *the public information channel* owing to better understanding of the implication of these public information for their firms than outside investors, drive insiders' profitable trades. Wang (2019) show that insiders will trade more profitably when the firm-specific information environment which is a proxy for private information is worsened. We proxy for the firm-specific stock informativeness using the Future Earnings Response Coefficient (FERC) proposed by Tucker and Zarowin (2006), the return synchronicity suggested by Piotroski and Roulstone (2004) and the intra-board link suggested by Crawford *et al.* (2020). We follow these previous works to construct three binary variables: (i) a $\mathrm{FERC}_{i,t}$ that is one for the top quintile of stocks whose current prices contain the most future earnings information and zero otherwise, and assume that these firms have better firm-specific information environment, (ii) $\mathrm{Synch}_{\mathrm{I,t}}$, to measure returns' synchronicity, equals to one for the bottom quintile of stocks whose current prices contain more firm-specific information and comove weakly with the current and lagged market and industry returns, and zero otherwise and (iii) $\mathrm{Com\_dir}_{\mathrm{j,t}}$ equals to one for the IT firms that share common directors with the target firm, zero other. We then employ $\mathrm{FERC}_{i,t}$, $\mathrm{Synch}_{\mathrm{I,t}}$ and $\mathrm{Com\_dir}_{\mathrm{j,t}}$ as the second moderator variables separately. We hypothesize that if insiders trade on their private (public) information, the predictability of the firm's performance should (not) vary with firm-specific stock informativeness or should (not) vary with intra-board link. We provide details of these measures in Appendix 5.

We replicate the Table 4, Table 6 and Table 8 by using these three dummy variables as the moderator variables. We find, but not report, that for all panels, the coefficients of triple-interaction terms are constantly insignificant. Therefore, we conclude that insiders are indeed trading on the public M&A announcement because the change in their trading activity, the change in their trading profitability, and the amount of information they incorporate into the current stock prices are all invariant with the firm-specific price informativeness and the intra-board link. They have better understanding of the M&A deal and its impact on their firm's business performance rather than their private information. Our results are consistent with Alldredge and Cicero (2015) who show that insiders with major customers generate higher abnormal return because they pay more attention to the operating performance of their customers, which is a piece of public information that they understand better.

I. Insider Trading on the CAR of their linked firms

In this section, we further investigate the relationship between the insider trading decision and the CAR of linked firms around the M&A announcement. We argued previously that insiders mainly trade on the public M&A announcement rather than their private information, and therefore we hypothesis that the CAR around the M&A announcement of the target firm will predict the insider trading activities in IT firms in the subsequent three months. Insider trading literature has shown that insiders predominantly trade in a contrarian fashion that they will decrease (increase) their holdings when their firms' returns are high (low), as they possess private information and trade against the market (Lakonishok and Lee, 2001; Cohen *et al.*, 2012). We assess whether they also use the same trading strategy when they trade on the public M&A announcement of their linked firms. We do not make a prediction because insiders can time the market and buy (sell) when the market has underreacted (overreacted).

We collapse all variables into firm level and include the CAR of both the target firms and IT firms in the regression. We focus both on the initial market return that is measured by CAR between day (-3,3), and the post-announcement CAR measured between day (4,14). The dependent variable is $NPV_{j,(0,2)}$ and we use the same set of control variables as in Table 9. Table 10 shows that insiders systematically trade on the $CAR_{j,(-3,3)}$ around the M&A announcement of their linked firms. The coefficient of $NPV_{j,(0,2)}$ is statistically significant 0.122, 0.241 and 0.182 for competitor, customer and supplier and statistic, respectively. These positive and significant coefficients mean that the higher the $CAR_{j,(-3,3)}$, the less insiders will sell in the next three months. The significant coefficient of $CAR_{j,(4,15)}$ suggests that the market reaction to the M&A is still a determinant for insiders' trading decision up to 15 calendar days after the announcement. On the other hand, insiders' do consider their firm's $CAR_{j,(4,15)}$ when they trade, only in customer relationships. Moreover, the previous univariate statistics have shown that the CAR of IT firms around the M&A announcement is significant but economically small, explaining the insignificant coefficients of $IT\_CAR_{j,(-3,3)}$ and $IT\_CAR_{j,(4,15)}$ in most columns, and indicating that outside investors fail to fully adjust the value of IT firms and recognize that the M&A deal will not substantially affect the business performance of IT firms.

Overall, these results further reaffirm that insiders primarily trade on the public information of their linked firms rather than the private information regarding their own firms. Insiders agree with the market as they trade in the same direction as the market, but they recognize the market has not fully incorporated the effect of the M&A deal into the stock price of the IT firm, so they increase (decrease) their holdings when the CAR is higher (lower).

[Insert Table 10 here]

J. Insider trading and profitability around M&A announcement of incomplete deals

We next assess whether unobservable shocks, which are correlated with the M&A announcements, drive our results. This would happen if, for instance, the motivation of the acquiror to take over the target firm is not observed by the market, but known by insiders who may trade on the private information to generate abnormal returns. We follow Boehm and Sonntag (2022) and find IT firm that is comparable in terms of the shocks but does not eventually experience any impact on its business performance. We use deals that have been announced but eventually withdrawn. We consider that, if there are omitted variables motivating insiders to trade, we would expect the same positive and significant relationship using the same diff-in-diff regression specification. On the other hand, if our previous results are correct, insiders are indeed trading on the change in their firms' performance after the deal has been completed, we would expect an insignificant relationship using the announcement of these incomplete deals because the business prospects remain the same for those IT firms. We obtain a list of withdrawn deals from SDC by applying the same filters, and we end up with 187 deals, which account for around one quarters of our complete M&A deal sample.

We replicate Table 4 and Table 6 using these withdrawn deals and report the regression results in Table 11 Panel A and Panel B, respectively. From the results, we can see that the coefficients of $Post \times Treat_{i,j}$ in Panel A and the coefficients of $Post \times Treat \times NPV_{i,j}$ in Panel B are inconsistent with our previous findings. In unreported results, we replicate Table 6 using these incomplete deals, and find none of the coefficients of $Post \times Treat \times NPV_{i,j}$ is statistically significant. To the extent that incomplete deals are a good comparison group to the complete deals, the increases in insider trading activity and profitability are not likely to be driven by the unobserved shocks. Furthermore, the approach is similar to the comparison of a placebo test with the actual treatment in a sense that these incomplete deals will not affect the future performance of IT firms, and therefore are not likely to motivate insiders to trade.

The explicit assumption behind these tests is that insiders from IT firms will have better insight regarding the probability of deal competition. Since these economically linked firms are closely involved in their daily operations, they may better predict the deal competition than the aggregate market. If our previous results are correct that insiders are trading on the future impact of the deal on their firms, they should be able to predict the deal completion probability as incomplete deals would not impact their firms. In the section, we re-specify a cross-section regression to explore the possibility.

First, we aggregate all the insider trading activities in IT firm *j* between month (0,2) to construct our main variable of interest, the net purchasing value $NPV_{j,(0,2)}$, the announcement of their linked firm is in month 0. For IT firms that have no insider trading transactions, the $NPV_{j,(0,2)}$ is set to 0. Then, we define the dependent variable CompletionD equals to one if the deal eventually completes and zero otherwise. To differentiate the deal completion probability estimated by corporate insiders and the market, we follow Fidrmuc and Xia (2022) which is built on Samuelson and Rosenthal (1986) and Fidrmuc, Roosenboom and Zhang (2018) to construct the market-measured deal completion probability denoted as Mkt_pro_t for target firm *t*. We compute two similar versions of Mkt_pro_t by following Samuelson and Rosenthal (1986) and Fidrmuc *et al.* (2018) separately. We report the result using the former but also use the latter measure to obtain the robust results. The construction details are in Appendix 6. The average Mkt_pro_t is 0.638 in our sample. We follow Fidrmuc and Xia (2022) and include a refined set of control variables representative of the factors that will affect the probability of deal completion. We include $Ln(makt\_cap)_{j,m}$, $illiq_{j,m-1}$, $bm_{j,m-1}$, $mom_{j,m,(d-1,d-365)}$, $sd_{j,(d-365,d-1)}$, $delta\_sd_{j,(m-3,m-1)}$, all calculated based on the target firm in the M&A deal month *m* announcement date *d* rather than the IT firm. Appendix 2 describes the construction of these variables. In addition, we include the 3-day CAR of target firms in our regression, and control for year and industry fixed effects (Fidrmuc and Xia, 2022).

Table 11 Panel C shows that NPV can predict the future deal completion probability for competitor and customer both at the 95% confidence level, and they cannot predict the future probability for supplier. The results further confirm that when insiders buy more after the M&A announcement, they will recognize the deal has higher probability of completion. On the other hand, when insiders do not significantly increase their NPV, the deal completion probability will be relatively lower. More importantly, the market-estimated probability is positive and statistically significant at the 99% confidence level for all three relationship types. These results are consistent with the previous findings that the aggregate market can correctly predict deal completion probability (Fidrmuc and Xia, 2022). The significant predictive power embedded in the insider trading in the economically linked firm is in addition to the market-estimated probability, implying the informational content embedded in the insider trading activity is not the same as the aggregate market, further support our previous findings that insiders have better understanding about the deal completion than the market. The coefficient of the target firm's 7-day CAR is positive and statistically significant at the 99% confidence level, indicating the better the market reacts to the M&A announcement, the higher the probability that the deal will be eventually completed. The results for the control variables are consistent with the previous findings and thus omitted for brevity. We also aggregate insider trading in each month rather than month (0,2) to investigate the timing of these informed insider trading. We report the results in column (2), (4) and (6). The coefficient of $NPV_{j,(0,0)}$ is quantitatively the same as $NPV_{j,(0,2)}$ for all three relationships, indicating that only the insider trading in the M&A announcement month embeds a strong predictive power for the future deal completion probability, their trading decisions in the next two months contain little predictive power.

[Insert Table 11 here]

K. Placebo Test

We re-estimate our baseline diff-in-diff regression using 1000 placebo tests. ×We describe the construction of placebo test in Appendix 7 and report the results in Table 12. The left-hand side of Table 12 shows that the average and median values of the interaction term $Post{\times}Treat_{i,j}$ are close to zero for both Table 4 and Table 6. Although the coefficient $Post{\times}Treat_{i,j}$ is negative and statistically significant at the 99% confidence level, its scale is economically small, consistent with the observation that there is a decreasing trend in the NPV with the passage of time. The coefficient of $Post{\times}Treat{\times}NPV_{i,j}$ remains statistically indifferent from zero when replicating Table 4. In the right-hand side of Table 12, we report the percentage of 1000 placebo tests. The coefficients of $Post{\times}Treat_{i,j}$ are statistically different from zero using a two-tailed t-test at the reported confidence level with a positive coefficient.

Table 12 indicates that our main findings are not driven by a random selected firms that do not have their economically linked firms become the target in a M&A deal. Relying on a binomial one-sided test, none of the proportions reported in the last three columns are statistically different from the theoretical threshold. Furthermore, none of the 1000 randomly selected sample produce both a statistically significant and positive coefficient of Post×Treat$_{i,j}$ for Table 4 and a statistically significant and positive coefficient of Post×Treat×NPV$_{i,j}$ for Table 6. These placebo tests indicate that it is extremely unlikely to find a significant increase in the insider net trading value as well as a significant increase in the insider trading profitability at the same time without being affected by shocks.

[Insert Table 12 here]

V. Conclusion

In the paper, we document that corporate insiders systematically reduce their sell transactions when their competitors or customers, but not their suppliers, become targets in M&A deals. Their transactions are uniformly profitable, indicating that corporate insiders better time their transactions when their firms are misvalued due to the limited attention constraint faced by the aggregate market. We investigate the informational content behind these informed transactions and show that these more informed insider transactions can support both productive efficiency hypothesis and purchasing efficiency hypothesis. We question the informational channel that these insiders are trading, we find that they trade on their better understanding about the public announcement of the M&A deal rather than the private information which the is the conventional source of insider information. Furthermore, insiders learn from the market reaction to the M&A announcement and will adjust their trading decisions based on the five-day CAR of the target firms, not the CAR of their own firms, the results reaffirm our findings that insiders are trading on the public rather than private information. We argue that if insiders are indeed trading in the future change in their business performance, we should not observe a significant change for M&A announcements that are eventually withdrawn. We subject our results to a battery of robustness test and find that incomplete M&A announcements do not lead to the significant change in both insider trading activity and profitability. Moreover, insider trading measure can predict the probability of the deal completion, and the predictive power is in addition to the market-estimated probability. Lastly, we show that our results are robust to the exclusion of the insider firms with many linked firms, and to the exclusion of firms that have many peer firms in the same four-digit SIC industry. Our results are unlikely to be driven by the inconsistency caused by reverse causality, and our conclusions cannot be replicated using 1000 placebo tests.

We also use different econometric specifications to address the endogeneity issue, which is one main concern in the insider trading literature by specifying a difference-in-difference regression based on a matched sample firm to isolate the M&A announcement effect. We also employ a two-stage least square (2SLS) estimator with the mutual fund hypothetical sales as an instrumental variable (IV) to consider the possible reverse causality that the M&A deal is induced by changes in the treated firm's fundamentals. However, we have not analyzed other than bid announcements of the IT and their economically liked firms, because of data constraint. The extent to which this will affect our results is the subject of further research.

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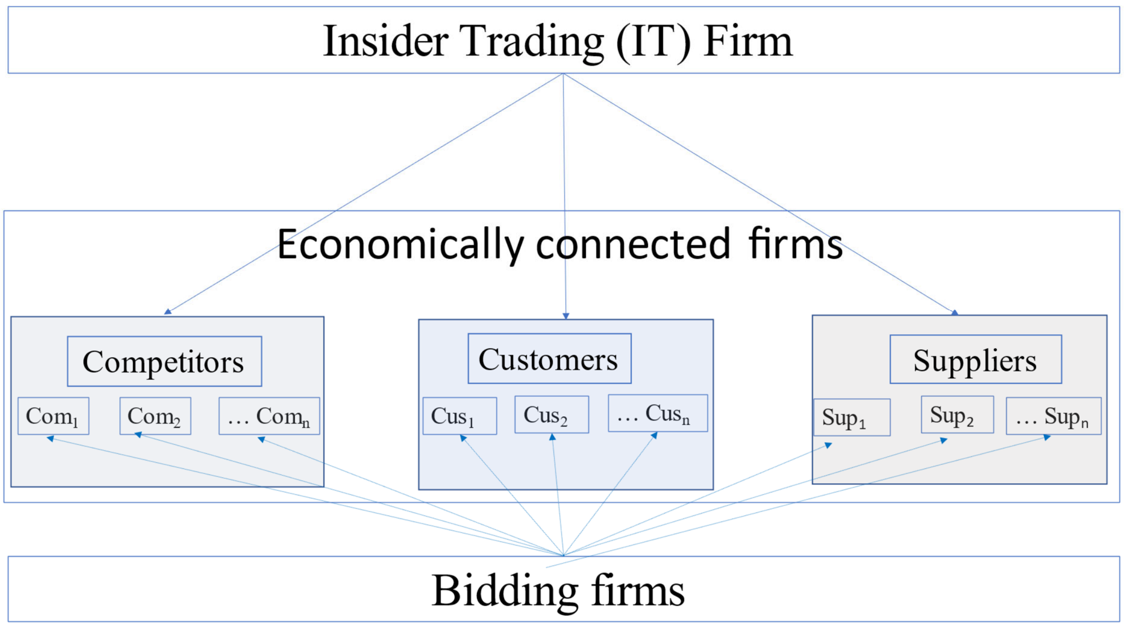
Figure 1: Research setting illustration



This figure summarizes our research setting. We refer to insider trading (IT) firms as companies where we focus on the trading by insiders after the announcement of takeover bids of their economically-connected firms – their competitors and/or supply chain firms (customers and suppliers). We specify that our IT firms have no link with the bidding firms.

Table 1: Descriptive statistics

Table 2 Panel A reports the summary statistics for the insider trading firms around month (-12, 2), M&A announcement is in month 0, we aggregate all insider transactions at monthly level. The row "Competitor", "Customer" and "Supplier" mean the M&A target firm is the competitor, customer or supplier of the insider firm, respectively. Panel B reports the cumulative abnormal return around the M&A announcement for deal target, acquiror and insider trading firms. We use the standard event study methodology to calculate CARs with the market model parameters estimated over 200 trading day period starting from day -240 relative to the M&A announcement date. We employ CRSP value-weighted index as the market return and require at least 100 trading days over the estimation window for a firm to be included in the sample. All firms reported in Panel B are not conditioning on there is at least one insider transactions in month (-12, 2). Appendix 2 details all the variables. ***, **, * indicate the sample mean is statistically different at the 99%, 95% and 90% confidence level, respectively. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

Panel A: Summary statistics for insider trading firms

	Competitor			**Customer**			**Supplier**		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
IT firm characteristics around month (-12, 2)									
$total\_asset_{j,t-1}$ (\$m)	17,542	2,016	73,235	14,573	1,170	50,596	53,099	8,131	155,649
$mkt\_cap_{j,m}$ (\$m)	14,235	2,834	31,136	16,595	2,022	37,755	26,053	10,789	42,042
$momentum_{j,m(d-365,d-1)}$	0.416	0.314	0.380	0.424	0.311	0.395	0.470	0.346	0.409
$illiq_{j,m-1}$	0.003	0.000	0.013	0.004	0.000	0.016	0.001	0.000	0.007
$bm_{j,m-1}$	0.416	0.314	0.380	0.424	0.311	0.395	0.470	0.346	0.409
$numest_{j,t-1}$	13	10	10	12	9	9	17	17	9
$Insti\_hold_{j,q}$	0.722	0.800	0.256	0.730	0.795	0.242	0.752	0.808	0.224
$Insti\_HI_{j,q}$	93.030	25.229	465.226	71.835	27.177	300.985	103.457	14.130	563.220
$roa_{j,t-1}$	0.014	0.045	0.161	0.010	0.039	0.143	0.039	0.044	0.100
$rd_{j,t-1}$	0.123	0.010	0.347	0.101	0.034	0.210	0.061	0.000	0.188
$leverage_{j,t-1}$	0.210	0.165	0.210	0.207	0.174	0.192	0.263	0.240	0.204
$age_{i,d,m}$	11.458	11.008	7.348	10.850	10.074	7.551	11.784	11.121	7.699

$\text{tenure}_{i,j,d,m}$	7.989	6.455	6.560	7.473	5.427	6.707	8.341	6.984	6.809
$\text{vol}_{j,(d-90,d-1)}$	0.652	0.472	0.574	0.620	0.456	0.536	0.705	0.509	0.618
$\text{sd}_{j,(d-365,d-1)}$	0.451	0.387	0.227	0.487	0.431	0.235	0.395	0.337	0.205
$\text{delta\_sd}_{j,(m-3,m-1)}$	-0.004	-0.007	0.169	-0.007	-0.012	0.180	-0.009	-0.011	0.144
Observations	2,862			1,709			2,189		
Deal and Relationships Characteristics									
No. Deals	457			287			318		
No. Relationships	1,106			598			812		
IT and target in the same 4-digit SIC	305(28%)			43(7%)			32(10%)		
IT and target in the same 2-digit SIC	683(62%)			133(22%)			145(18%)		
Diversification Deal (Bidder unrelated to Target)	385(84%)			252(88%)			270(84%)		
Target Market Cap 4-weeks ago ($m)	2,494	609	6,639	4,415	1,090	8,964	2,690	533	6,774
Deal Value ($m)	3,329	800	9,006	6,001	1,557	12,123	3,578	687	8,929
Tender Offer	0.178	0.000	0.383	0.133	0.000	0.341	0.192	0.000	0.395
Bid premium (%)	37.5	30.18	34.83	34.05	28.13	32.86	37.00	31.5	33.10
Insider trading measure between month (-6,-1)									
NPV	-0.505	-1.000	0.857	-0.545	-1.000	0.833	-0.634	-1.000	0.767
Distinct Insider	1,397			794			1029		
Distinct Firms	875			480			566		

Panel B: CAR around M&A announcement unconditional on insider trading									
	Competitor			**Customer**			**Supplier**		
	CAR(-30,-2)	CAR(-1,1)	CAR(2,30)	CAR(-30,-2)	CAR(-1,1)	CAR(2,30)	CAR(-30,-2)	CAR(-1,1)	CAR(2,30)
Target Firm	0.050***	0.271***	-0.006	0.057***	0.255***	-0.002	0.051***	0.259***	-0.004
	(0.008)	(0.013)	(0.005)	(0.009)	(0.013)	(0.005)	(0.009)	(0.013)	(0.005)
Sample	481	481	480	396	395	395	385	384	385
IT Firm	-0.005	0.007***	-0.005*	-0.000	0.002*	-0.000	-0.002	0.000	0.002
	(0.004)	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.002)	(0.000)	(0.002)
Sample	3,251	3,251	3,249	1,762	1,762	1,754	2,726	2,725	2,725
Acquiror Firm	-0.007	-0.011*	-0.017*	-0.070	-0.013**	-0.031***	-0.016*	-0.015**	-0.025**
	(0.007)	(0.006)	(0.010)	(0.009)	(0.006)	(0.010)	(0.009)	(0.006)	(0.011)

Sample	221	221	221	221	177	177	165	165	165

Table 2: Summary statistics around M&A announcement

Panel A reports the summary statistics of the treated and matched firms on the basis of the last six months' cumulative returns, book-to-market and the logarithm of market capitalization at the end of month -1. We restrict that the control firm will not have any of its competitor, customer or supplier became the target in the month (-12, 12) with month 0 as the M&A announcement month. $Sum\_NPV_{(-6,-1)}$ is the NPV calculated by aggregating all insider transactions for a given insider between month (-6, -1). Column (3), (6) and (9) report the t-test results by assuming unequal variance between treated and control firms for insider purchase and sell transaction, respectively. Panel B compares the monthly insider trading activities between treated and control firms.

Panel A: Summary statistics for treated and control firms									
	Competitor			Customer			Supplier		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Treated	Matched	Diff	Treated	Matched	Diff	Treated	Matched	Diff
$Sum\_NPV_{(-6,-1)}$	-0.478	-0.486	0.008	-0.570	-0.591	0.021	-0.641	-0.629	-0.123
	(0.026)	(0.021)	(0.033)	(0.031)	(0.025)	(0.040)	(0.028)	(0.022)	(0.036)
$Sum\_NPV_{(-12,-1)}$	-0.504	-0.511	0.007	-0.575	-0.605	0.031	-0.694	-0.661	-0.032
	(0.023)	(0.020)	(0.030)	(0.028)	(0.024)	(0.037)	(0.023)	(0.021)	(0.031)
$bm_{j,m-1}$	0.492	0.477	0.015	0.474	0.457	0.016	0.499	0.496	0.003
	(0.012)	(0.010)	(0.015)	(0.015)	(0.012)	(0.019)	(0.014)	(0.011)	(0.018)
$ret6_{j,m,(d-1,d-180)}$	0.067	0.081	-0.014	0.090	0.095	-0.005	0.068	0.078	-0.009
	(0.008)	(0.007)	(0.010)	(0.010)	(0.009)	(0.013)	(0.007)	(0.006)	(0.009)
$Ln(makt\_cap)_{j,m}$	7.454	7.296	0.158**	7.493	7.382	0.111	8.806	8.430	0.376***
	(0.049)	(0.048)	(0.069)	(0.067)	(0.057)	(0.088)	(0.075)	(0.065)	(0.099)
$roa_{j,t-1}$	-0.028	-0.009	-0.019*	0.006	-0.000	0.007	0.032	0.032	0.001
	(0.009)	(0.005)	(0.010)	(0.005)	(0.008)	(0.009)	(0.005)	(0.005)	(0.007)
$BHAR\_m\_30_{i,d}$	0.005	-0.001	0.006	0.004	0.001	0.003	-0.012	0.002	-0.010*
	(0.005)	(0.002)	(0.006)	(0.006)	(0.003)	(0.007)	(0.005)	(0.002)	(0.006)
$BHAR\_ff\_30_{i,d}$	0.001	-0.001	0.002	0.002	-0.000	0.002	-0.020	-0.002	-0.018***
	(0.005)	(0.002)	(0.006)	(0.005)	(0.003)	(0.006)	(0.005)	(0.002)	(0.006)
Panel B: Insider trading around M&A announcement month (0,2)									
NPV	-0.488	-0.550	0.061**	-0.581	-0.673	0.091*	-0.731	-0.608	-0.123***
$BHAR\_m\_30_{i,d}$(Buy)	-0.004	-0.006	0.002	0.051	0.005	0.047***	0.032	-0.009	0.041**
$BHAR\_m\_30_{i,d}$(Sell)	-0.006	0.001	-0.007*	-0.007	0.003	-0.010*	0.002	0.002	0.00
$BHAR\_ff\_30_{i,d}$(Buy)	0.016	-0.008	0.024**	0.045	-0.000	0.045***	0.026	-0.009	0.035***
$BHAR\_ff\_30_{i,d}$(Sell)	-0.006	0.001	-0.007*	-0.008	0.002	-0.010*	0.001	0.003	-0.002

Table 3: Insider trading activity around M&A announcement

This table reports the diff-in-diff regression result. The dependent variable is the monthly $NPV_{i,m}$. $(Post \times Treat)_{i,t}$ is a dummy variable equals to one for firms that have a linked firms become the target in a M&A deal in month *m*, and zero otherwise. In column (2), (4) and (6), we exclude the top quintile samples and their corresponding control firms with the most competitor, customer, and supplier, respectively. $Competitor_{j,t}$,$Customer_{j,t}$,$Supplier_{j,t}$ is dummy equal to one if the target firm is acquiror's competitor, customer or supplier, respectively Appendix 2 details all the variables. We include sample in pre-announcement month (-12,-1) and post-announcement period (0,2). Standard errors reported in parentheses are computed based on robust standard errors clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Competitor		**Customer**		**Supplier**	
	All	No top quintile	All	No top quintile	All	No top quintile
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	NPV	NPV	NPV	NPV	NPV	NPV
$TreatD_{i,j}$	0.085**	0.080*	0.105**	0.102	0.062	0.068
	(0.037)	(0.048)	(0.052)	(0.063)	(0.040)	(0.045)
$PostD_{i,j}$	-0.001	0.012	-0.001	-0.026*	0.041***	0.044***
	(0.010)	(0.012)	(0.011)	(0.013)	(0.015)	(0.016)
$(Post \times Treat)_{i,t}$	0.044**	0.045**	0.062**	0.072**	-0.016	-0.018
	(0.021)	(0.023)	(0.024)	(0.031)	(0.023)	(0.026)
$Ln(makt\_cap)_{j,m}$	-0.201***	-0.208***	-0.163***	0.065	-0.125**	-0.094
	(0.040)	(0.046)	(0.057)	(0.059)	(0.058)	(0.063)
$mom_{j,m.(d-1,d-365)}$	-0.128***	-0.102***	-0.085**	-0.115***	-0.112***	-0.116***
	(0.034)	(0.034)	(0.035)	(0.030)	(0.037)	(0.041)
$Competitor_{j,t}$	0.043**	0.067***	0.020	0.037	-0.131	-0.008
	(0.017)	(0.021)	(0.016)	(0.029)	(0. 011)	(0.013)
$Customer_{j,t}$	0.081	0.072	-0.031	-0.034	0.046	0.041
	(0.051)	(0.055)	(0.024)	(0.024)	(0.045)	(0.055)
$Supplier_{j,t}$	-0.100***	-0.132***	0.002	0.001	0.041*	0.037
	(0.034)	(0.048)	(0.015)	(0.014)	(0.025)	(0.027)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Insider FE	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.07	0.07	0.05	0.04	0.05	0.06
Sample	7,276	6,399	4,240	3,103	5,122	4,351

Table 4: M&A target firm heterogeneity

This table report the diff-in-diff regression result by interacting five moderators with$Post\times Treat_{i,j}$. The regression specification is the same as in Table 3. The dependent variable is $NPV_{i,m}$ computed at the monthly level. $(Post\times Treat)_{I,t}$ is a dummy variable equals to one for firms that have a linked firms become the target in a M&A deal in month *m*, and zero otherwise. In Panel A, the moderator variable is $homo_{i,j}$, an dummy variable equal to one for industry that is not selling differentiated goods as defined by Rauch (1999), zero otherwise. In Panel B, the moderator variable is $innov_{i,j}$, an dummy variable equal to one for the top quantile of firms that receive most of USPTO patent each year, zero otherwise. In Panel C, D, E, F and G, the moderator variable is top, a dummy variable equal to one for the top quantile of firms that have most competitors, supplier and customers, the highest bid premium and the highest percentage of stock financing, respectively, and zero otherwise. These moderators are calculated for the target firm in the M&A deal. We include all control variables and all main and interaction terms, but omit their coefficients for brevity. Appendix 2 details all the variables. We only include sample in pre-announcement month (-12,-1) and post-announcement period (0,2). We control for firm, month-year and person fixe effects in all panels. Standard errors reported in parentheses are computed based on robust standard errors clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Panel A: Homogeneous product producer-Rauch (1999)		
	Competitor	Customer	Supplier
	(1)	(2)	(3)
Dependent Variable	NPV	NPV	NPV
$Post\times Treat_{i,j}$	0.028	0.063**	-0.018
	(0.021)	(0.026)	(0.023)
$Post\times Treat^{*}homo_{i,j}$	0.381**	-0.025	0.185**
	(0.188)	(0.062)	(0.081)
Control Variables	Yes	Yes	Yes
	Panel B: Innovative target firm-top quantile for patent received		
$Post\times Treat_{i,j}$	0.051**	0.064**	-0.008
	(0.022)	(0.028)	(0.023)
$Post\times Treat^{*}innov_{i,j}$	-0.224**	0.028	-0.239**
	(0.114)	(0.081)	(0.116)
Control Variables	Yes	Yes	Yes
	Panel C: Target firm with many competitors-top quantile for number of competitors		
$Post\times Treat_{i,j}$	0.018	0.040	-0.041
	(0.022)	(0.027)	(0.026)
$Post\times Treat^{*}top_{i,j}$	0.087*	0.128**	0.088*

	(0.052)	(0.061)	(0.050)
Control Variables	Yes	Yes	Yes
	Panel D: Chain complexity-number of suppliers		
Post×Treat$_{i,j}$	0.052**	0.034	0.003
	(0.023)	(0.024)	(0.024)
Post×Treat*top$_{i,j}$	-0.117**	0.400***	-0.112*
	(0.057)	(0.130)	(0.063)
Control Variables	Yes	Yes	Yes
	Panel E: Target firm with many customers -top quantile for number of customers		
Post×Treat$_{i,j}$	0.020	0.013	-0.030
	(0.021)	(0.024)	(0.024)
Post×Treat*top$_{i,j}$	0.206*	0.243**	0.106*
	(0.107)	(0.113)	(0.059)
Control Variables	Yes	Yes	Yes
Within R^2	0.07	0.06	0.05
Sample	7,276	4,240	5,122
	Panel F: Bid Premium		
Post×Treat$_{i,j}$	0.049**	0.079***	-0.018
	(0.022)	(0.030)	(0.025)
Post×Treat*top$_{i,j}$	-0.138**	-0.103*	0.009
	(0.062)	(0.056)	(0.048)
Control Variables	Yes	Yes	Yes
Sample	7,212	4,155	5,074
	Panel G: Percentage of consideration paid in stocks		
Post×Treat$_{i,j}$	0.009	0.075***	0.004
	(0.021)	(0.029)	(0.023)
Post×Treat*top$_{i,j}$	0.155**	-0.095	-0.113
	(0.075)	(0.058)	(0.077)
Control Variables	Yes	Yes	Yes
Sample	7,210	4,286	5,145

Table 5: Insider trading return around M&A announcement

Table 6 reports the diff-in-diff regression output. $(Post \times Treat)_{i,m}$ is a dummy variable equals to one for firms that have a CEO turnover in year t, and zero otherwise. Appendix 2 details all the variables. We only include sample in pre-announcement month (-12,-1) and post-announcement period (0,2). We control for all main levels of interactions terms. Standard errors reported in parentheses are computed based on robust standard errors clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Competitor		**Customer**		**Supplier**	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	$BHAR\_m\_30_{i,d}$	$BHAR\_ff\_30_{i,d}$	$BHAR\_m\_30_{i,d}$	$BHAR\_ff\_30_{i,d}$	$BHAR\_m\_30_{i,d}$	$BHAR\_ff\_30_{i,d}$
$TreatD_{i,j}$	-0.007	-0.006	-0.029	-0.023	0.011	0.011
	(0.010)	(0.011)	(0.021)	(0.024)	(0.012)	(0.011)
$PostD_{i,j}$	-0.011**	-0.010	-0.018**	-0.020**	-0.002	-0.003
	(0.005)	(0.006)	(0.008)	(0.008)	(0.006)	(0.006)
$Post \times Treat_{i,j}$	0.028**	0.032**	0.039**	0.042**	0.042***	0.042***
	(0.013)	(0.013)	(0.015)	(0.017)	(0.014)	(0.014)
$Post \times Treat \times NPV_{i,j}$	0.029**	0.034***	0.039***	0.046***	0.028**	0.027**
	(0.013)	(0.013)	(0.015)	(0.017)	(0.014)	(0.013)
$NPV_{i,j}$	0.014**	0.014**	0.011	0.009	-0.000	0.000
	(0.007)	(0.007)	(0.012)	(0.014)	(0.008)	(0.008)
$Ln(makt\_cap)_{j,m}$	-0.048***	-0.060***	-0.071***	-0.094***	-0.068***	-0.073***
	(0.011)	(0.016)	(0.019)	(0.026)	(0.015)	(0.017)
$mom_{j,m.(d-1,d-365)}$	-0.043***	-0.045***	-0.039***	-0.035**	-0.039***	-0.040***
	(0.010)	(0.011)	(0.014)	(0.017)	(0.012)	(0.014)
$bm_{j,m-1}$	-0.032	-0.037	0.036*	0.043*	0.010	0.008
	(0.021)	(0.027)	(0.020)	(0.026)	(0.024)	(0.023)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.05	0.06	0.08	0.08	0.08	0.08
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Insider FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	6,113	6,065	3,527	3,482	4,222	4,199

Table 6: Two-stage least square regression for insider trading activity

This table reports two-stage least square estimator in Panel A and Panel B to replicate Table 2 and Table 3, respectively. We use $MFHS_{(j,t)}$ as our instrumental variable by following Boehm and Sonntag (2022). We describe the construction of the IV in detail in Appendix 4. Our endogenous variable is $TreatD_{(i,j)}$ and all the interaction terms between $TreatD_{(i,j)}$ and other variables. We only report the first-stage regression output without the inclusion of endogenous interaction terms to show the predictability of our IV for $TreatD_{(i,j)}$. We report the Kleibergen-Paap Wald F Statistic for the first stage regression at the bottom of each panel. *K-P Wald F ($TreatD_{(i,j)}$)* and *K-P Wald F (All)* denotes the first-stage regression by excluding and including the endogenous interaction term $\widehat{Tre} * PostD_{(i,j)}$, respectively. The coefficients of these control variables are omitted for brevity. Standard errors reported in parentheses are computed based on robust standard errors clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Panel A: Insider Trading Activity					
	Competitor		Customer		Supplier	
	1st Stage	2nd Stage	1st Stage	2nd Stage	1st Stage	2nd Stage
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	$TreatD_{(i,j)}$	NPV	$TreatD_{(i,j)}$	NPV	$TreatD_{(i,j)}$	NPV
$MFHS_{j,t}$	0.046***		0.205***		0.041***	
	(0.007)		(0.024)		(0.010)	
$PostD_{i,j}$		-0.029		-0.044**		0.002
		(0.019)		(0.020)		(0.022)
$\widehat{TreatD}_{i,j}$		-0.873		-0.296*		-0.501
		(0.535)		(0.169)		(0.559)
$\widehat{Tre} * PostD_{i,j}$		0.131**		0.203**		0.076
		(0.060)		(0.091)		(0.066)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Insider FE	Yes	Yes	Yes	Yes	Yes	Yes
K-P Wald F ($TreatD_{i,j}$ Only)	41.17***		74.10***		18.38***	
K-P Wald F (All)	19.79***		36.86***		9.22***	
Sample	11,771	11,771	6,876	6,876	8,545	8,545
	Panel B: Insider Trading Profitability					
Dependent Variable	$TreatD_{(i,j)}$	$BHAR\_m\_30_{i,d}$	$TreatD_{(i,j)}$	$BHAR\_m\_30_{i,d}$	$TreatD_{(i,j)}$	$BHAR\_m\_30_{i,d}$
$MFHS_{j,t}$	0.049***		0.145***		0.042***	
	(0.009)		(0.015)		(0.011)	
$PostD_{i,j}$		-0.013**		-0.016**		-0.009
		(0.006)		(0.008)		(0.007)
$\widehat{TreatD}_{i,j}$		-0.145		-0.017		0.293*
		(0.134)		(0.068)		(0.158)
$Post*\widehat{Tre}D_{i,j}$		0.034*		0.054*		0.040*
		(0.020)		(0.030)		(0.024)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Insider FE	Yes	Yes	Yes	Yes	Yes	Yes
K-P Wald F ($TreatD_{i,j}$ Only)	32.05***		28.04***		15.52***	
K-P Wald F (All)	15.50***		13.66***		7.94***	
Sample	9,446	9,446	5,518	5,518	6,798	6,798

Table 7: Informational content behind insider transactions

Table 8 reports the fixed effect regression output based on matched sample. In Panel A, the dependent variable is the change in return on asset between year t and year t+2. In Panel B, the dependent variable is the change in the earnings surprise between the quarter q+4 and the quarter q+5 proposed by DellaVigna and Pollet (2009). In Panel C, the dependent variable is the change in sale between year t and year t+2. In Panel D, the dependent variable is the change in the unit cost of a new patent scaled by research and development cost between year t and year t+3. In Panel E, the dependent variable is the change in the cost of goods sold scaled by sale between year t and year t+2. We include the same set of control variables as in Table 3. The coefficients of these control variables are omitted for brevity. We include firm, month-year and insider fixed effects in all panels. Standard errors reported in parentheses are computed based on robust standard errors clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Panel A: Change in return on asset					
	Change in return on asset (0,2)			Change in return on asset (0,2) excluding the top quintile		
	(1)	(2)	(3)	(4)	(5)	(6)
	Competitor	Customer	Supplier	Competitor	Customer	Supplier
$Post \times Treat_{i,j}$	0.018**	0.021**	-0.003	0.024**	0.026**	-0.002
	(0.008)	(0.009)	(0.009)	(0.010)	(0.011)	(0.011)
$Post \times Treat \times NPV_{i,j}$	0.015*	0.019**	0.005	0.021**	0.025**	0.009
	(0.008)	(0.009)	(0.009)	(0.010)	(0.012)	(0.011)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Sample	6,074	3,432	4,453	4,784	2,742	3,843
	Panel B: Earnings Surprise					
	$Earnings\ Surprise_{(q+4,q+5)}$			$Earnings\ Surprise_{(q+4,q+5)}$ excluding the top quintile		
	Competitor	Customer	Supplier	Competitor	Customer	Supplier
$Post \times Treat_{i,j}$	0.017	0.006	0.042	0.031*	0.012	0.061*
	(0.014)	(0.006)	(0.025)	(0.018)	(0.009)	(0.033)
$Post \times Treat \times NPV_{i,j}$	0.025*	0.010**	0.044*	0.043**	0.016**	0.062**
	(0.014)	(0.005)	(0.024)	(0.021)	(0.008)	(0.031)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Sample	6,722	3,861	4,952	5,270	2,787	4,100
	Panel C: Sale Growth					
	Sale_growth(0,2)			Sale_growth(0,2) excluding the top quintile		
	Competitor	Customer	Supplier	Competitor	Customer	Supplier
$Post \times Treat_{i,j}$	0.027	0.063**	-0.038	0.044**	0.059**	-0.042
	(0.020)	(0.031)	(0.023)	(0.019)	(0.030)	(0.031)

Post×Treat×$NPV_{i,j}$	0.039**	0.080***	-0.031	0.049***	0.092***	-0.039
	(0.020)	(0.031)	(0.023)	(0.019)	(0.030)	(0.030)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Sample	6,835	3,669	4,798	5,378	2,721	3,969

Panel D: Change in the unit cost of a patent						
	Change in the unit cost of a patent (0,3)			Change in the unit cost of a patent (0,3) (exclude top quintile)		
	Competitor	Customer	Supplier	Competitor	Customer	Supplier
Post×$Treat_{i,j}$	-1.069**	-1.308	1.179*	-1.066*	-1.979	1.817*
	(0.545)	(1.162)	(0.693)	(0.629)	(1.418)	(0.938)
Post×Treat×$NPV_{i,j}$	-1.163**	-1.063	1.183*	-1.150**	-2.217	1.653*
	(0.536)	(1.195)	(0.702)	(0.576)	(1.476)	(0.948)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Sample	5,775	3,185	4,252	4,591	2,322	3,479

Panel E: Change in the cost of goods sold						
	Change in COGS(0,2)			Change in COGS(0,2) (exclude top quintile)		
	Competitor	Customer	Supplier	Competitor	Customer	Supplier
Post×$Treat_{i,j}$	-0.015	-0.020	0.016	-0.040	-0.009	-0.013
	(0.056)	(0.017)	(0.022)	(0.076)	(0.019)	(0.015)
Post×Treat×$NPV_{i,j}$	-0.182***	-0.033*	0.006	-0.231**	-0.024	0.015
	(0.071)	(0.018)	(0.021)	(0.103)	(0.016)	(0.028)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Sample	6,216	3,763	4,586	4,875	2,771	3,772

Panel F: Less alternative suppliers in the same four-digit SIC industry (Supplier Only)					
	Δroa (0,2)	Earnings Surprise$_{(q+4,q+5)}$	Δsale(0,2)	Δcost of patent(0,3)	ΔCOGS(0,2)
Post×Treat×$NPV_{i,j}$	0.010**	0.006	0.040**	-0.650	-0.074*
	(0.005)	(0.012)	(0.020)	(0.580)	(0.040)
Control Variables	Yes	Yes	Yes	Yes	Yes
Within R^2	0.32	0.03	0.31	0.08	0.22
Sample	1,395	1,530	1,481	1,327	1,534

Table 8: Propensity of IT firm's future M&A activity within one year

The table presents the coefficient estimates for a series of fixed effect regressions investigate the relationship between the net insider trading value between months (0,2) and the likelihood that their firms become a target or acquiror between months (3,14). The binary dependent variables are equal to one if the IT firm becomes a target (column 1, 3 and 5) or a bidder (column 2,4 and 6), and zero otherwise. $NPV_{j,(0,2)}$ is the NPV by aggregating all transactions from a given insider between months (0, 2), their linked firms become the target in a deal in month 0. Other control variables refer to independent variables we found to be insignificant and thus omitted for brevity: $roa_{j,t-1}$, $sale\_growth2y_{j,t-1}$, $rd_{j,t-1}$, $leverage_{i,t-1}$, $cash\_ratio_{j,t-1}$, $concentration_{i,t-1}$, $industryROA\Delta_{i,j-1}$, $mom_{j,m,(d-1,d-365)}$, $ind\_activity_{j,(m-1,m-12)}$ and constant. Appendix 2 details all the variables. We control for month-year fixed effect in all columns. Standard errors reported in parentheses are computed based on Hubert-White robust standard errors. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Competitor		**Customer**		**Supplier**	
	$TargetD_j$	$AcquirorD_j$	$TargetD_j$	$AcquirorD_j$	$TargetD_j$	$AcquirorD_j$
	(1)	(2)	(3)	(4)	(5)	(6)
$NPV_{j,(0,2)}$	0.017^{**}	-0.010	0.011^{**}	-0.006	0.032^{***}	-0.038^{*}
	(0.007)	(0.016)	(0.005)	(0.023)	(0.012)	(0.021)
$total\ asset_{j,t-1}$	0.003	0.018^{***}	-0.003	0.011^{***}	-0.008^{***}	0.011^{*}
	(0.002)	(0.004)	(0.002)	(0.004)	(0.003)	(0.006)
$runup_{j,m,(d-30,d-1)}$	-0.052^{**}	-0.016	-0.005	-0.024	0.030	-0.012
	(0.023)	(0.032)	(0.026)	(0.070)	(0.057)	(0.046)
$illiq_{j,m}$	-0.039	0.081^{*}	-0.004	0.097	-0.334^{*}	-0.024
	(0.036)	(0.042)	(0.003)	(0.223)	(0.194)	(0.664)
$bm_{j,t-1}$	0.004	-0.023^{**}	-0.015	-0.005	0.002	-0.019
	(0.008)	(0.009)	(0.009)	(0.022)	(0.011)	(0.012)
$tobinq_{j,t-1}$	-0.009^{***}	-0.001	-0.003	0.001	-0.008^{*}	-0.003
	(0.002)	(0.002)	(0.003)	(0.006)	(0.004)	(0.005)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.026	0.031	0.018	0.022	0.030	0.013
Sample	1,342	1,342	821	821	974	974

Table 9: Insider trading on the CAR of target firm around the announcement date

Table 10 presents the coefficient estimates for a series of fixed effect regressions investigate the relationship between the net insider trading value between months (0,2) and the CAR of linked firms. We use the standard event study methodology to calculate CAR. The market model parameters are estimated over the 200-trading day period starting at day -240 relative to the M&A announcement date. We employ the CRSP value weighted index as the market return and require at least 100 trading days over the estimation window for a firm to be included in the sample. Other control variables refer to independent variables we omitted for brevity are: $cash\_ratio_{j,t-1}$, $tobinq_{j,t-1}$, $bm_{j,t-1}$, $mom_{j,m.(d-1,d-365)}$, $roa_{j,t-1}$, $illiq_{j,m}$, $sale\_growth2y_{j,t-1}$, $rd_{j,t-1}$, $leverage_{i,t-1}$, $concentration_{i,t-1}$, $industryROA\Delta_{i,j-1}$ and constant. Appendix 2 details all the variables. Standard errors reported in parentheses are computed based on Hubert-White robust standard errors. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Competitor		**Customer**		**Supplier**	
	$NPV_{j,(0,2)}$		$NPV_{j,(0,2)}$		$NPV_{j,(0,2)}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$Target\_CAR_{j,(-3,3)}$	0.122***		0.241**		0.182*	
	(0.047)		(0.123)		(0.106)	
$Target\_CAR_{j,(4,15)}$		0.118***		0.302**		0.202**
		(0.045)		(0.123)		(0.098)
$IT\_CAR_{j,(-3,3)}$	0.207		-0.205		-0.424	
	(0.192)		(0.127)		(0.280)	
$IT\_CAR_{j,(4,15)}$		0.119		0.703***		-0.219
		(0.143)		(0.267)		(0.354)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.09	0.08	0.11	0.16	0.07	0.08
Sample	902	902	420	420	636	639

Table 10: Insider trading activity and profitability around withdraw M&A announcements

The table Panel A and Panel B report the diff-in-diff regression output based on a list of M&A deal that has been announced but withdrawn. We replicate Table 3 in Panel A and Table 4 in Panel B. In both Panel A and B, we control for firm, month-year and insider fixed effects. We control for the same set of control variables as in Table 3 and 4, but omit their coefficients for brevity. Standard errors are clustered at the firm-month level. Panel C reports the cross-sectional fixed effect regressions investigate the relationship between the net insider trading value between months (0,2) and the likelihood that the deal in which their economically linked firm has become the target will complete. The binary dependent variables are equal to one if the deal is complete, and zero otherwise. $NPV_{j,(0,2)}$ is the NPV by aggregating all transactions from a given insider between months (0, 2), their linked firms become the target in a deal in month 0. Mkt_pro_t is the probability of the deal completion calculated based on market reaction to the M&A announcement for target firm t calculated based on Samuelson and Rosenthal (1986) and Fidrmuc and Xia (2022). $Target\_CAR_{j,(-3,3)}$ is the seven day cumulative abnormal return (CAR) around the M&A announcement date for the target firm. We use the standard event study methodology to calculate CAR. The market model parameters are estimated over the 200 trading day period starting at day -240 relative to the M&A announcement date. We employ the CRSP value weighted index as the market return and require at least 100 trading days over the estimation window for a firm to be included in the sample. Other control variables refer to independent variables we omit for brevity: $Ln(makt\_cap)_{j,m}$, $illiq_{j,m-1}$, $bm_{j,m-1}$, $mom_{j,m,(d-1,d-365)}$, $sd_{j,(d-365,d-1)}$, $delta\_sd_{j,(m-3,m-1)}$ and constant. These control variables are calculated based on target firms with day *d* as the M&A announcement date. We control for IT firm and 2-dig SIC industry fixed effects. Appendix 2 details all the variables. Standard errors reported in parentheses are computed based on Hubert-White robust standard errors. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Panel A: Insider Trading Activity					
	Competitor		Customer		Supplier	
	All	No top quintile	All	No top quintile	All	No top quintile
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	NPV	NPV	NPV	NPV	NPV	NPV
$Post{\times}Treat_{i,j}$	-0.052	-0.054	0.022	0.063	0.05	0.001
	(0.042)	(0.052)	(0.035)	(0.054)	(0.041)	(0.036)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.051	0.056	0.068	0.080	0.102	0.010
Sample	2,061	1,661	1,846	1,325	1,734	1,466
	Panel B: Insider Trading Profitability					
	Competitor		Customer		Supplier	
Dependent Variable	$BHAR\_m\_30_{i,d}$	$BHAR\_ff\_30_{i,d}$	$BHAR\_m\_30_{i,d}$	$BHAR\_ff\_30_{i,d}$	$BHAR\_m\_30_{i,d}$	$BHAR\_ff\_30_{i,d}$
$Post{\times}Treat_{i,j}$	-0.026	-0.021	0.029	0.005	-0.017	-0.008
	(0.022)	(0.019)	(0.043)	(0.053)	(0.027)	(0.031)
$Post{\times}Treat{\times}NPV_{i,j}$	-0.039*	-0.052**	0.017	0.031	-0.016	-0.011

	(0.023)	(0.026)	(0.047)	(0.051)	(0.026)	(0.299)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.085	0.069	0.103	0.128	0.11	0.126
Sample	1,680	1,671	1,513	1,510	1,432	1,416

Panel C: Insider Trading Activity and the probability of deal completion

	Competitor		Customer		Supplier	
Dependent Variable	CompletionD	CompletionD	CompletionD	CompletionD	CompletionD	CompletionD
$NPV_{j,(0,2)}$	0.053^{**}		0.089^{**}		-0.022	
	(0.026)		(0.040)		(0.029)	
$NPV_{j,(0,0)}$		0.053^{**}		0.093^{**}		-0.034
		(0.026)		(0.040)		(0.031)
$NPV_{j,(1,1)}$		-0.002		0.002		-0.041
		(0.029)		(0.046)		(0.032)
$NPV_{j,(2,2)}$		-0.002		0.012		0.025
		(0.029)		(0.046)		(0.032)
Mkt_pro_t	0.020^{***}	0.020^{***}	0.027^{***}	0.027^{***}	0.057^{***}	0.057^{***}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.012)	(0.012)
$Target\_CAR_{j,(-3,3)}$	0.311^{***}	0.311^{***}	0.329^{***}	0.333^{***}	0.321^{***}	0.326^{***}
	(0.047)	(0.047)	(0.086)	(0.088)	(0.057)	(0.057)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.067	0.067	0.106	0.106	0.101	
Sample	1,262	1,262	709	709	899	899

Table 11: Placebo Tests

The table Panel A reports the results of a placebo test on 1000 random samples of 840 firms drawn from the TR U.S company population after excluding firms whose economically linked firms become the target of a M&A deal. The left-hand side of the table reports the mean, median, standard deviation (SD) and skewness (Skew) of the distribution of the coefficients of the $\text{Post}\times\text{Treat}_{i,j}$ and $\text{Post}\times\text{Treat}\times\text{NPV}_{i,j}$, estimated using the same diff-in-diff regression specification in Table 3 and Table 5. We match the pseudo-treated firm with one control firms by matching on the last six-month return, size and book-to-market ratio in the same calendar month with the shortest Mahalanobis distance. The right-hand side of the table reports the percentage of 1000 random samples of 840 firms that reject the null hypothesis of the diff-in-diff coefficient is equal to zero at the 1%, 5% and 10% levels in favor of the alternative hypotheses of being significantly positive. Relying on a binomial one-sided test-statistics, none of the proportions are statistically different from the corresponding theoretical threshold. For the last two rows, we focus on the sample that report both statistically significant and positive coefficient for $\text{Post}\times\text{Treat}_{i,j}$ and $\text{Post}\times\text{Treat}\times\text{NPV}_{i,j}$ when replicating Table 3 and Table 4, respectively.

	Dependent variable	**Replicated Tables**	**Coefficient**				**% Statistically significant positive coefficient**		
			Mean	Median	SD	Skew	1%	5%	10%
$\text{Post}\times\text{Treat}_{i,j}$	NPV	3	-0.0014***	-0.001	0.015	-0.307	0.002	0.006	0.007
$\text{Post}\times\text{Treat}\times\text{NPV}_{i,j}$	$\text{BHAR\_m\_30}_{i,d}$	4	0.000	0.000	0.017	-0.067	0.005	0.036	0.060
$\text{Post}\times\text{Treat}\times\text{NPV}_{i,j}$	$\text{BHAR\_ff\_30}_{i,d}$	4	0.001	0.001	0.017	-0.048	0.007	0.039	0.060
$\text{Post}\times\text{Treat}_{i,j}$	$\text{BHAR\_m\_30}_{i,d}$	4	0.014	0.011	0.010	0.983	0.005	0.035	0.057
$\text{Post}\times\text{Treat}_{i,j}$	$\text{BHAR\_ff\_30}_{i,d}$	4	0.014	0.011	0.010	0.994	0.007	0.032	0.066
$\text{Post}\times\text{Treat}\times\text{NPV}_{i,j}$ and $\text{Post}\times\text{Treat}_{i,j}$ are both positive	NPV and $\text{BHAR\_m\_30}_{i,d}$	$\text{Post}\times\text{Treat}_{i,j}$ for table 4 and $\text{Post}\times\text{Treat}\times\text{NPV}_{i,j}$ for table 6					0.000	0.000	0.000
$\text{Post}\times\text{Treat}\times\text{NPV}_{i,j}$ and $\text{Post}\times\text{Treat}_{i,j}$ are both positive	NPV and $\text{BHAR\_f\_30}_{i,d}$	$\text{Post}\times\text{Treat}_{i,j}$ for table 4 and $\text{Post}\times\text{Treat}\times\text{NPV}_{i,j}$ for table 6					0.000	0.000	0.000

Appendix 1: Sample composition

Panel A: Sample Construction		
	Change in Sample Size	Sample Size
Total US domestic M&A deals from SDC (2003-2020)		169,298
Less		
Deal value under 1 million ($)	111,548	57,750
Nonpublic Target	39,517	18,233
Deal Type: Exchange Offers, Repurchases, Spin-off, Minority Stake Purchases, Recapitalization, Acquisitions of Remaining Interest, Privatisation, Restructuring, Reverse Takeover, Acquisition of Certain Assets, Buyback	13,349	4,884
Percent of shares held at announcement <= 49.99%	4	4,880
Percent of shares acquiror is seeking to own after transaction: >=50%	64	4,816
Deals that are announced for the same target within 730 days	428	4,388
Deals in which target firms have no relationship in FactSet Revere	3,122	1,266
Deals in which IT firms are also connected to the acquiror	37	1,229
Deals in which IT firms have more than one of their linked firms become target within 360 days	48	1,181
Deals that are not completed or partially completed	226	955
Deals in which linked firms have missing data or IT firms fail to match a control firm	261	694
IT firms that report no insider transactions in the entire history of TR	9	685
Final sample		685

Panel B: M&A sample distribution by M&A announcement year		
Announcement year	Number of Deals	% Of Sample
2003	12	1.75
2004	13	1.90
2005	20	2.92
2006	21	3.07
2007	25	3.65
2008	13	1.90
2009	21	3.07
2010	30	4.38
2011	27	3.94
2012	26	3.80

2013	44	6.42
2014	66	9.64
2015	68	9.93
2016	75	10.95
2017	62	9.05
2018	62	9.05
2019	56	8.61
2020	41	5.99

Panel C: Industry classifications of IT and target firms %

Fama-French 17 industry classification	**Competitor**		**Customer**		**Supplier**	
	IT	Target	IT	Target	IT	Target
Food	2.17	1.54	3.34	1.34	4.31	1.6
Mining and Minerals	0.45	0.09	0.33	0.00	0.25	0.86
Oil and Petroleum Products	2.90	2.53	3.18	3.35	2.96	1.6
Textiles, Apparel & Footwear	0.72	0.54	1.51	0.50	2.46	0.99
Consumer Durables	1.36	1.36	2.68	0.67	1.85	0.49
Chemicals	1.90	1.99	0.50	0.84	1.35	1.85
Drugs, Soap, Perfumes, Tobacco	5.16	7.78	5.52	3.02	4.68	3.69
Construction and Construction Materials	2.44	3.16	2.84	2.85	2.71	2.46
Steel Works Etc.	0.81	0.72	1.00	1.17	0.99	1.23
Fabricated Products	0.54	0.54	0.84	0.17	0.49	0.37
Machinery and Business Equipment	13.85	11.3	20.74	8.54	12.07	14.29
Automobiles	1.54	1.45	0.67	1.17	2.71	0.86
Transportation	1.90	2.08	4.01	3.18	3.69	2.83
Utilities	2.35	2.98	2.17	4.52	6.53	2.59
Retail Stores	9.23	11.66	1.84	19.60	9.85	0.86
Banks, Insurance Companies, and Other Financial Institutions	9.68	8.86	5.52	6.53	10.34	3.82
Other	42.99	41.41	43.31	42.55	32.76	59.61

Appendix 2: Definition of Variables

Variable Notation	Data Source	Definition
total asset$_{j,t-1}$	Compustat	Logarithm of the total asset (Compustat: at) in the last fiscal year.
mkt_cap$_{j,m}$	CRSP	Market capitalization value of a given stock at the end of day *d.*
Ln(mkt_cap)$_{j,m}$	CRSP	Logarithm of the market capitalization value of a given stock at the end of day *d.*
BHAR_m_30$_{i,d}$	CRSP	30-calendar day Buy-N-Hold return adjusted by using the CRSP value-weighted market index. Defined as the following: $BHAR_{m_n} = \prod_{t=1}^{d}[1 + R_{jt}] - \prod_{t=1}^{d}[1 + R_{mt}]$
BHAR_ff_30$_{i,d}$	CRSP, French's website	30-calendar day Buy-N-Hold return adjusted by using the NYSE size-decile portfolio.
NPV$_{i,m}$	Thomson Reuter Insider Filling	Net purchasing value for insider transactions in month *m* executed by insider *i*, calculated as the ratio of the net dollar amount of insider transactions over the total dollar amount of insider transactions. If *NPV_i* is greater (less) than 0, we recognize that the insider *i* is net buying (selling).
mom$_{j,m,(d-1,d-365)}$	CRSP	The cumulative raw return from (d-365, d-1), insider transaction occurs in day d.
ret6$_{j,m,(d-1,d-180)}$	CRSP	The cumulative raw return from (d-180, d-1) for firm *j* at the end of month m.
illiq$_{j,m-1}$	CRSP	Amihud's (2002) measure of illiquidity for firm *j* at the end of the last month. The measure is calculated as the monthly average of the daily ratio of absolute stock return to dollar volume.
bm$_{j,m-1}$	CRSP, Compustat	The book-to-market ratio calculated as the ratio of last fiscal year's book value over the market capitalization in the last trading day in December. Book value is computed as the following. Book value is equal to stockholder equity + deferred taxes and investment tax credit (Compustat: txditc, zero if missing) −preferred stock value. Stockholder equity is parent stockholder equity (Compustat: seq), or total common equity (Compustat: ceq) plus total preferred stock capital (Compustat: pstk) or the difference between the total asset (Compustat: at) and total liability (Compustat: lt), in that order, as available. Preferred stock value is the preferred stock redemption value (Compustat: pstkrv), or preferred stock liquidation value (Compustat: pstkl), or total preferred stock capital (Compustat: pstk), or zero, in that order as available. Negative bm ratio is restricted to zero. The ratio is calculated for firm *j* at the end of the last month.
numest$_{j,t-1}$	I/B/E/S	Analyst coverage is defined as the number of analysts that report a forecast for the next 1-

		fiscal year earnings per share for firm *j* at the end of the last month. If there is no earning forecast, the analyst coverage is set to be zero.
$\text{insti\_hold}_{j,q}$	Thomson Reuter 13F Holding	Percentage of shares owned by institution investors over total shares outstanding.
$\text{insti\_HI}_{j,q}$	Thomson Reuter 13F Holding	Herfindahl index based on the number of institution investors invested in stock *j*. We divide the number by 100 for reporting clarity.
$\text{roa}_{j,t-1}$	Compustat	Return on asset calculated as the net income (Compustat: ni) after taking out preferred dividend (Compustat: dvp), over the total asset (Compustat: at) for firm *j* at the end of the last fiscal year.
$\text{rd}_{j,t-1}$	Compustat	Research and development expense calculated as the research and development expense (Compustat: xrd) over sales (Compustat: sale) for firm *j* at the end of the last fiscal year. If Compustat reports missing research and development expense, it is set to be zero.
$\text{leverage}_{j,t-1}$	Compustat	Long term debt (Compustat: dltt) plus debt in current liability (Compustat: dlc) over the total assets (Compustat: at)
$\text{size}_{j,m-1}$	CRSP	The logarithm of market capitalization defined as adjusted stock price times adjusted shares outstanding for firm *j* at the end of the last month. The number is reported in a million.
$\text{age}_{i,d,m}$	Thomson Reuter Insider Filling	The date difference between the first occurrence of insider *i* in Smart insider database and the current transaction date *d* at the end of month *m*.
$\text{tenure}_{i,j,d,m}$	Thomson Reuter Insider Filling	The date difference between the date of the first transaction of insider *i* in firm *j* in Smart insider database and the current transaction date *d* in the firm *j* at the end of month *m*.
$\text{vol}_{j,(d-90,d-1)}$	CRSP	The total normalized trading volume in the last 90 trading days. Daily trading volume is normalized using the total share outstanding times 1,000
$\text{sd}_{j,(d-365,d-1)}$	CRSP	Annualized standard deviation of stock return computed over day (-365, -181). Day 0 is the insider trading day
$\text{delta\_sd}_{j,(m-3,m-1)}$	CRSP	The change between standard deviation computed over day (-180, -1) and over day (-365, -181).
competitorD_{r}	FactSet Revere, SDC	Dummy variable equals to one if acquiror is a competitor of target firm, zero otherwise.
customerD_{r}	FactSet Revere, SDC	Dummy variable equals to one if acquiror is a customer of target firm, zero otherwise.
supplierD_{r}	FactSet Revere, SDC	Dummy variable equals to one if acquiror is a supplier of target firm, zero otherwise.
$\text{MFHSD}_{j,t}$	Thomson Reuter and CRSP Mutual Fund	In each year, we divide all firms covered by both Thomson Reuter and CRSP mutual fund files according to their mutual fund hypothetical sales constructed by Edmans *et al.*(2012), Dessaint *et al.* (2019) and Boehm and Sonntag (2022) into quintiles. We create a dummy

		variable $MFHSD_{(j,t)}$ equal to one if the firm has been in the bottom quintile in year *t*, zero otherwise.
$MFHS_{j,t}$	Thomson Reuter and CRSP Mutual Fund	A continuous variable equals to the market capitalization weighted average $MFHSD_{j,t}$ of all linked firms in year t for a given relationship type. If control firm does not have any linked firm in a given year, the variable is set to be zero.
tobin's $Q_{i,t-1}$	Compustat	Market value of equity plus book value of debt-deferred tax over book value of total assets. $$\frac{(at + csho \times prcc\_f - ceq - txdb)}{at}$$
$concentration_{i,t-1}$	Compustat	The ratio of sales of the largest four firms to the total three-digit SIC industry sales (Cornett *et al.,* 2011 and Davis *et al.,* 2021)
$industryROA\Delta_{i,j-1}$	Compustat	The change in the industry return on asset over the next 12 months following the announcement month of linked firm becomes target (Davis *et al.,* 2021).
$cash\_ratio_{j,t-1}$	Compustat	The ratio between cash and short-term investments to the total asset (Cornett *et al.,* 2011 and Davis *et al.,* 2021). $$\frac{che}{at}$$
$sale\_growth2y_{j,t-1}$	Compustat	The change in the firm's sale over the previous 2 fiscal years (Cornett *et al.,* 2011 and Davis *et al.,* 2021).
$runup_{j,m,(d-30,d-1)}$	CRSP	The cumulative raw return from (d-30, d-1) at the end of month *m* for firm *j*.
$ind\_activity_{j,(m-1,m-12)}$	SDC	The total number of deal announcement in the same 2-dig SIC industry for firm j between month (-1,-12). If no deal is found, the value is zero.
$\mathbf{Com\_dir_{j,t}}$	Boardex	A dummy variable equals to one if IT firm shares a common director with target firms, and zero otherwise.
$SUE_{q,j}$	IBES	$$SUE_{q,j} = \frac{actual\_earnings_{q,j} - expected\_earnings_{q,j}}{price_{q,j}}$$ $SUE_{t,k}$ is the standardized unexpected earnings announced by firm *j* for quarter *q*, $actual\_earnings_{q,j}$ is the actual earnings per share for firm *j* for quarter *q*, and $expected\_earnings_{q,j}$ is the corresponding median of all analysts' earnings per share forecasts issued closest to in time to the earnings announcement date, but not more than 90 days prior to the fiscal period end. We normalize the $SUE_{q,j}$ by $price_{q,j}$ for firm *j* at the end of the quarter *q*.

Appendix 3: Event-type difference-in-difference regression

We follow Angrist and Pischke (2009) and Cengiz *et al.* (2019) to conduct an event-study type diff-in-diff regression and formally test on the parallel trend assumption. Variable pre_m equal to 1 for treated firms in month *m,* the month in our event window with month *0* as the M&A announcement month, and zero otherwise. post_m is defined with the same logic. The coefficients of Pre_m should be all statistically insignificant for the parallel trend assumption to hold. Pre_{-1} is omitted to avoid perfect multicollinearity. We control for firm, person, and month-year fixed effects. Standard errors are clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Competitor		**Customer**		**Supplier**	
	(1)	(2)	(3)	(4)	(5)	(6)
	NPV	$\text{BHAR\_m\_30}_{i,d}$	NPV	$\text{BHAR\_m\_30}_{i,d}$	NPV	$\text{BHAR\_m\_30}_{i,d}$
pre_{-12} …	0.006	-0.007	-0.013	-0.008	0.063	0.013
	(0.042)	(0.010)	(0.042)	(0.016)	(0.048)	(0.012)
pre_{-8}	0.038	0.016	0.014	-0.012	0.026	0.027^{**}
	(0.048)	(0.012)	(0.040)	(0.015)	(0.043)	(0.012)
pre_{-7}	-0.003	0.003	-0.019	0.000	0.020	0.018
	(0.046)	(0.010)	(0.041)	(0.016)	(0.043)	(0.011)
pre_{-6}	0.027	0.012	-0.013	-0.004	0.062	0.005
	(0.042)	(0.012)	(0.041)	(0.019)	(0.046)	(0.012)
pre_{-5}	0.054	-0.017	0.010	-0.001	0.052	0.012
	(0.048)	(0.011)	(0.043)	(0.015)	(0.049)	(0.013)
pre_{-4}	0.041	-0.004	0.036	-0.005	0.088	-0.002
	(0.041)	(0.010)	(0.038)	(0.013)	(0.066)	(0.011)
pre_{-3}	0.066	-0.008	0.020	-0.008	0.088	0.007
	(0.042)	(0.010)	(0.033)	(0.016)	(0.054)	(0.011)
pre_{-2}	0.051	-0.005	0.042	-0.021	0.016	0.017
	(0.045)	(0.010)	(0.039)	(0.016)	(0.048)	(0.013)
post_0	0.100^{**}	0.020^{**}	0.028	-0.014	0.072^{*}	0.033^{**}
	(0.048)	(0.010)	(0.037)	(0.015)	(0.040)	(0.013)
post_1	0.054	0.010	0.093^{*}	-0.025	0.049	0.029^{**}
	(0.047)	(0.012)	(0.051)	(0.019)	(0.053)	(0.014)
post_2	0.064	-0.013	0.102^{**}	0.033^{**}	0.062	0.023^{**}
	(0.040)	(0.010)	(0.046)	(0.015)	(0.044)	(0.011)
Other Control	Yes	Yes	Yes	Yes	Yes	Yes
Sample	7741	6503	4479	3806	5230	4133

Appendix 4: Construction of mutual fund hypothetical sales instrument

The instrumental variable (IV) used in the paper is the mutual fund hypothetical sales (MFHS). We follow the Appendix C of Dessaint *et al.* (2019) which is based on the Edmans *et al.* (2012). The IV has been successfully applied in Boehm and Sonntag (2022) . We use both the CRSP mutual funds data and Thomson Reuter Mutual Fund data which is formerly known as the CDA Spectrum/Thomson to construct the IV.

First, we begin with the CRSP mutual funds data which reports the monthly return and total net assets by asset class *k.* We compute the weighted average return of fund *j* in month *m* of year *t* using the total net asset (TNA) by asset class as the weight.

$$Return_{j,m,t} = \frac{\sum_k (TNA_{k,j,m,t} \times Return_{k,j,m,t})}{\sum_k TNA_{k,j,m,t}}$$

where *k* indexes asset class. We compound these returns to obtain quarterly returns. Furthermore, we estimate the net inflow into fund *j* in quarter *q* of year *t,* as a fraction of its beginning-of-quarter net assets, as follows:

$$flow_{j,q,t} = \frac{TNA_{j,q,t} - TNA_{j,q-1,t} \times \left(1 + Return_{j,q,t}\right)}{TNA_{j,q-1,t}}$$

Second, we use Thomson Reuter to obtain the share holdings $shares_{j,i,q,t}$ of each fund *j* in firm *i* at the end of quarter *q* of year *t.* Finally, we compute the hypothetical sales of fund *j*'s assets in firm *i* for all mutual funds for which $flow_{j,q,t} < -0.05$, as follows:

$$MFHS_{i,q,t}^{dollars} = \sum_j (flow_{j,q,t} \times shares_{j,i,q-1,t} \times price_{i,q-1,t})$$

We obtain share price and trading volume from CRSP. This variable is the hypothetical net selling of stock *i*, in dollar value, by all mutual funds that subject to extreme capital outflows. We further normalize $MFHS_{i,q,t}^{dollars}$ by the dollar value of total trading volume in stock *i* in quarte *q* of year *t* as follows:

$$MFHS_{i,t} = \sum_{q=1}^{q=4} \frac{MFHS_{i,q,t}^{dollars}}{VOL_{i,q,t}}$$

Appendix 5: Construction of FERC and stock return synchronicity

We follow Tucker and Zarowin (2006) and Wang (2019) to construct the FERC by first estimating the following equation:

$$R_{i,t} = \alpha + \beta_0 X_{i,t-1} + \beta_2 X_{it} + \beta_3 (X_{i,t+1} + X_{i,t+2} + X_{i,t+3}) + \beta_3 R_{i,t+3} + \varepsilon_{i,t}$$

where $X_{i,t}$ is the basic annual earnings per share excluding extraordinary items (*epspx*), adjusted for stock splits and stock dividends and deflated by the stock price at the beginning of the fiscal year *t.* $R_{i,t}$ is the firm's annual return beginning at the fiscal year *t* and $R_{i,t+3}$ is a three-year future return for the firm from fiscal year *t+1* to *t+3.* The coefficient of the sum of the future three-year earnings per shares β_3 is the FERC. We truncate all variables at the top and bottom 1%. A higher β_3 means the current stock return impounds more future earnings information and is more informative for future earnings and *vice versa.* We follow Wang (2019) to estimate a rolling panel regression using the trailing 36 months across each two-digit SIC industry. We restrict that there are at least 8 (24) months in $R_{i,t}$ ($R_{i,t+3}$) for a stock to be included in the regression and create binary variable FERC that is one for the top quintile of the β_3 and zero otherwise.

As in Piotroski and Roulstone (2004), we estimate the stock return synchronicity from the following equation:

$$\mathrm{FirmRET}_{i,t} = \alpha + \beta_1 \mathrm{MktRET}_{j,t} + \beta_2 \mathrm{MktRET}_{j,t-1} + \beta_3 \mathrm{IndRET}_{k,t} + \beta_4 \mathrm{IndRET}_{k,t-1} + \varepsilon_{i,t}$$

where $MktRET_{j,t}$ is the market return proxied by the CRSP value-weighted buy-and-hold market return in year t. $IndRET_{k,t}$ is the value-weighted average industry buy-and-hold return identified using the two-digit SIC code in year *t*. We estimate the regression for each firm-year observation with weekly return data and restrict a minimum of 45 weekly observations each year. The synchronicity is measured as $\ln\left(\frac{R^2}{1-R^2}\right)$. The R^2 is the R square of the above regression. A higher $Synch_{i,t}$ indicates the current firm return comove strongly with the current and lagged market and industry returns, which further indicates the stock price contains less firm-specific information.

Appendix 6: Construction of the deal completion probability

To differentiate the marginal predicative power of net insider trading in deal completion probability from the probability estimated by the aggregate market, we follow Fidrmuc and Xia (2022) estimate the market probability of deal completion which is based on Samuelson and Rosenthal (1986) who argue that the market's assessment on the deal completion probability will reflect on the target stock prices after the M&A deal announcement because the larger the price difference between the target stock price on a day *d* and the offer price $\mathrm{p_{of}} - \mathrm{p_d}$, the higher the probability that the deal will be completed. If the stock price immediately jumps to the offer price, then the market reckons that the deal will be completed with certainty. On the other hand, a little change in price no higher than the fall back price, $\mathrm{p_f}$, will imply that the market assesses the likelihood of deal completion is almost zero. Fidrmuc and Xia (2022) show that the price on day *d* is $\mathrm{p_d} = \mathrm{q} \times \mathrm{p_{of}} - (1 - \mathrm{q}) \times \mathrm{p_f}$. *q* denotes the probability of deal completion. The *q* can be obtained by rearranging the equation as $q = (\mathrm{p_d} - \mathrm{p_f})/(\mathrm{p_{of}} - \mathrm{p_f})$

In the study, we follow Fidrmuc and Xia (2022) to set *d* equal to 1 which is the next trading day after the announcement date. To estimate the *q*, we employ two similar but different methods. For the first method, we follow Samuelson and Rosenthal (1986) to estimate the fall back price as the weighted average of $\mathrm{p_{-42}}$ which is the stock price 42 trading days before the announcement and $\mathrm{p_{of}}$: $\mathrm{p_f} = 0.63 \times \mathrm{p_{-42}} + 0.37 \times \mathrm{p_{of}}$. The deal completion probability is then computed as $q = (\mathrm{p_{+1}} - \mathrm{p_f})/(\mathrm{p_{of}} - \mathrm{p_f})$. We denote the estimated probability as $\mathrm{Mkt\_pro_j}$ report the result in Table 7 Panel C. In further robustness checks, we tried weight of (0.5, 0.5) and (0.72, 0.25), all results in Table 7 Panel C remain the robust.

For the second method, we follow Fidrmuc *et al.* (2018) to estimate probability *q*. Fidrmuc *et al.* (2018) assumes that the target price unaffected by the deal announcement, and the equation simplifies to $\mathrm{q} = (\mathrm{p_{+1}} - \mathrm{p_{-42}})/(\mathrm{p_{of}} - \mathrm{p_{-42}})$. We do not report the result using this version of estimated probability but all results in Table 7 Panel C remain robust.

Appendix 7: Construction of placebo tests

To confirm that our findings are not due to chance and the inappropriateness of matching logarithm, we re-estimate our baseline diff-in-diff regression using 1000 placebo tests. We randomly select 840 firm-year observations to be considered as treated firms. We choose 840 pseud-event firms as we are focusing on the average number of treated firms across three types of relationships. To be comparable to the true event treatment effect and avoid biases due to the M&A announcement of economically linked firms, we restrict these pseud-event firms do not have any their economically linked firms become a target of a M&A deal in the month (-12, 0). For each test, we repeat our matching algorithm to select one nearest neighbor in the same calendar month in terms of last six-month return, size and book-to-market ratio using the shortest Mahalanobis distance. For each of the 1000 tests, we replicate Table 4 and Table 6 and compute the test statistics associated with the two-tailed α significance level of the interaction term, $\text{Post}\times\text{Treat}_{i,j}$ and $\text{Post}\times\text{Treat}\times\text{NPV}_{i,j}$.