Algorithmic Trading in Rivals

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Abstract

This paper investigates the role of algorithmic trading in generating cross-stock information linkages around corporate earnings announcements. We find that computer-initiated net order flows in rival stocks have information content for announcing-firm returns. Consistent with the notion that algorithmic traders are attentive investors, algorithmic order flows become substantially more informative during the announcing day. We also show that algorithmic trading is more likely to occur across stocks when announcing firms are larger than rivals and when rival firms are more liquid than announcers. Overall, our study highlights that algorithmic traders facilitate cross-stock information transmission by initiating information-based trades in the stocks of rival firms.

JEL classifications: G10, G14, G20
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1. Introduction

This paper investigates the role of algorithmic trading in generating cross-stock information linkages during the periods around corporate earnings announcements. Our study is inspired by two strands of research. The first strand highlights that computerized trading activity reflects an informational advantage. Such an advantage may arise from the fact that computer algorithms collect and process information more quickly than humans (e.g., Biais and Woolley, 2011; Chaboud et al., 2014). Technological advances reduce the monitoring frictions and enable algorithmic traders to acquire information about market conditions more efficiently, imposing information asymmetry on other investors who are slower in analysing the market environment (Hendershott and Riordan, 2013).[1] Advance information can also be obtained by purchasing early access to market data (along with colocation and other high speed technologies).[2] Empirical evidence suggests that the liquidity demanding trades of one particular type of algorithmic traders who engage in high frequency trading strategies predict short-term price movements (Brogaard et al., 2014) and anticipate and trade ahead of other investors' order flow (Hirschey, 2013).[3] Some theories also regard fast (algorithmic) traders

[1] Biais et al.'s (2010) model holds a similar view that trading algorithms mitigate cognition limits of humans. See also Biais and Woolley (2011) for a detailed discussion on that computers reduce investor inattention. In addition, Biais et al.'s (2015) model builds on the similar notion that firms investing in fast trading technologies empower them to obtain advance information by rapidly scanning the market environment, generating adverse selection costs on other slow investors.

[2] See, for example, Easley et al. (2015) for further details discussion about that worldwide exchanges now sell market data to investors, and in particular, their clients who specialize in high frequency trading. Easley et al. (2015) suggest that this practice enable some traders to see the market data before other investors. O'Hara (2015, p7) claims that it "turns public information into private information".

[3] See, for example, Zhang (2013) and Brogaard et al. (2015) for further empirical evidence regarding algorithmic traders' informational advantage.

as informed agents who utilize their speed advantage to accelerate the access to advance information (Biais et al., 2015) or to trade on their forecast before others react to the news (Foucault et al., 2015).[4] In addition, computer algorithms have been widely employed by traditional informed agents (e.g., institutional investors) to minimize execution costs (e.g., Australian Securities Exchange, 2010; Hendershott et al., 2011; Hasbrouck and Saar, 2013).[5] While current research suggests that algorithmic trading may improve the informational efficiency of prices (e.g., Hendershott et al., 2011; Brogaard et al., 2014; Chaboud et al., 2014), it is less understood about the impact of algorithmic trading on the price discovery process with multiple stocks settings.

We are further motivated by the second strand of research that highlights that information-based trading is likely to occur across stocks (e.g., Caballé and Krishnan, 1994; Tookes, 2008; Jiang et al., 2009; Akbas et al., 2015; Pasquariello and Vega, 2015). This line of research argues that informed traders may choose to trade strategically across stocks to camouflage any informational advantage and reduce the market impact of trading. In particular, Tookes (2008) claims that firm-specific news of one particular company may affect its competitors, creating incentives for informed traders to initiate information-based

[4] O'Hara (2015, p7) maintains that nowadays "informed trading is multidimensional in that traders can know more about the asset or about the market (or markets) or even about their own order flow and use this information to take advantage of liquidity providers."

[5] In particular, the algorithms are employed by (the brokers of) buy-side institutions to decide where and how much to trade. Given that their objective is mainly about executing a desired position change, this type of algorithmic trading activity essentially demands liquidity (Hasbrouck and Saar, 2013). Further, for the notion that institutions are informed, see Badrinath et al. (1995), Sias and Starks (2007), Irvine et al. (2007), and Boehmer and Kelley (2009). The most recent study by Hendershott et al. (2015) suggests that institutions are informed about news.

trades in the stocks of rival firms. The key empirical implication of cross-stock trading hypothesis is that order flows in the stocks of non-announcing rivals can contemporaneously impact the returns of the announcing firms (e.g., Tookes, 2008; Akbas et al., 2015; Pasquariello and Vega, 2015). We incorporate the cross-stock trading incentives into the analysis of the informational role of algorithmic traders. Our study addresses Brogaard et al.'s (2014, p2304) call for study of the "cross-stock, cross-market, and cross-asset behaviours of high frequency traders". We argue that if algorithmic traders have the informational advantage over human investors, and information-based trading is likely to occur across stocks, then algorithmic traders should have incentives to exploit their informational advantage by trading strategically in the related stocks.

Utilizing a proprietary data set that precisely pinpoints computer-initiated transactions on the Australian equity market, we examine whether algorithmic traders choose to initiate information-based trades in industry rivals of the announcing firms. The "industry rivals" are identified according to product market competition literature (e.g., Tookes, 2008) by selecting any stocks in the same industry as the announcing stocks when there has no other news that is released in the same industry within a specified time frame. Similar to that of Tookes (2008) and Pasquariello and Vega (2015), we infer the information content of algorithmic trading in rivals by estimating the cross-stock price impacts of computer-initiated net order flows during the periods around corporate earnings announcements. We find that the algorithmic order flows in rival stocks have information content for announcing-firm returns, while human-initiated net order flows remain uninformative. In particular, the computer-initiated transactions generate significant cross-stock price impacts during the period immediately before the firm-specific earnings announcements. Our results support the conjecture that algorithmic traders have incentives to exploit their informational advantage in the stocks of rival firms and their subsequent trades facilitate information transmission across stocks. Further, we also show that the cross-stock algorithmic order flows become substantially more informative about announcing-firm returns during the announcing day, suggesting that the information flows from stocks of rival firms to announcing firms are further enhanced by algorithmic trading during the period in which it is known that the firm-specific information is publicly released. Our announcing-day results are different from that of Tookes (2008) in which the cross-stock information transmission on the announcing day remains largely unchanged. In light of the notion that computers collect and interpret information more efficiently than humans, one can interpret our findings as that algorithmic traders pay close attention to public announcements on the economically linked firms and their subsequent trades improve information linkages across stocks. Our results are in line with the attentive informed trading hypothesis of Alldredge and Cicero (2014) in which certain traders possess informational advantage in their ability of learning the full impact of public announcements on the related stocks while other investors remain relatively inattentive.[6]

Our paper takes into consideration the strength and the nature of the informational relatedness between announcers and rivals when analysing the cross-stock algorithmic trading. We show that computer-initiated net order flows in the informationally related competitors (i.e., any industry rivals significantly co-move with the announcing stocks) generate higher impacts on the announcers' returns. Our findings are similar to that of Akbas

[6] In reality, some initially uninformed while sophisticated algorithmic traders may gain informational advantage by observing informed trading that occurs across stocks, and their subsequent trades should also generate information linkages across stocks. Nevertheless, Tookes (2008, p399) stress that "what matters in this analysis is the location in which these traders choose to transact, not how a particular trader becomes informed. If sophisticated traders choose to make cross-stock trades given their superior information, they would facilitate information transmission in ways that are consistent with the main model".

et al. (2014) and Jiang et al. (2009) who suggest that the strength of the economic relatedness between two firms determines the degree of the cross-stock price impact. Next, by measuring the nature of informational relatedness based on the idiosyncratic return co-movements in De Bodt and Roll (2014), we find that that algorithmic order flows in business partners (competitors) of the announcing firms generate significant positive (negative) cross-stock price impacts.

We further validate our hypothesis by considering the cross-sectional predictions of Tookes' (2008) model in which informed traders are more willing to trade in the smaller rival stocks because product market competition implies that these stocks are more vulnerable to the news on economically linked competitors. Consistent with the cross-sectional implication of Tookes (2008), our results show that algorithmic order flows in rivals only generate significant impacts on announcing-firm returns when the market capitalizations of announcing firms are larger than that of rivals. In addition, we also find that the cross-stock algorithmic trading produces significant price impacts when rival stocks are more liquid than announcers. This supports the notion that algorithmic traders tend to initiate trades when the market is deep (Hendershott and Riordan, 2013) and that information-based trading is more likely to occur in liquid stocks that provide better camouflage (Kyle, 1985). Overall, our cross-sectional evidence highlights that algorithmic traders are more likely to trade across stocks when their informational advantage could be better exploited in the rival stocks.

Last but not least, our paper extends the analysis by considering both the unexpected component in earnings announcements and the timing of the news releases. We also separate the analysis of cross-stock price impacts into the liquidity demanding and liquidity supplying side of each trade, respectively. First, by measuring earnings surprises based on announcers' cumulative abnormal return (CAR) similar to the notion of Ball and Brown (1968), we show that the algorithmic order flows generate significant cross-stock price impacts for the high

CAR group (i.e., greater unexpected earnings) during all periods. In contrast, algorithmic order flows are only informative during the announcing-day window for low CAR group (i.e., smaller earnings surprises). Second, we demonstrate that the announcing-day algorithmic order flows in rivals are only informative when the earnings news is released during trading hours, a scenario when algorithmic traders are more likely to differentiate from humans investors in the terms of the information processing skills. Third, our paper highlights that algorithmic traders facilitate cross-stock information transmission into prices when computers initiate the trades. Consistent with the arbitrage strategies in the "concept release" of U.S. Securities and Exchange Commission (SEC, 2010), we show that the cross-stock price impacts are only significant during the announcing-day window when computers take liquidity from humans. This also supports the notion that algorithmic traders speedily capture the inefficiencies through liquidity demanding orders, imposing adverse selection costs to slow traders (Brogaard et al., 2014; Chaboud et al., 2014). Overall, our findings support the view that algorithmic trading improves informational efficiency of prices through liquidity demanding orders by accelerating the price discovery process. Our results are robust after the inclusion of autocorrelations and cross-autocorrelations terms to control for transient non-informational effects (Hasbrouck, 1991), lagged adjustment to the recent price changes in rival stocks (Chan, 1993), and any reversal of contemporaneous price impacts over longer lagged order flows (Tookes, 2008; Pasquariello and Vega, 2015). Our findings are also robust to market-wide effects (King and Wadhwani, 1990; Hasbrouck and Seppi, 2001) and to using alternative time interval to calculate net order flows.

To the best of our knowledge, this is the first study highlighting that algorithmic traders may choose to initiate information-based trades in the stocks of rival firms around individual firm news announcements. Prior studies on the informational role of algorithmic traders (e.g., Brogaard et al. (2014) on individual stocks; and Chaboud et al. (2014) in the foreign exchange market) suggest that computerized trading activity may enhance the informational efficiency of prices. Our study compliments previous research by taking into consideration the cross-stock trading incentives of algorithmic traders. We show that computer-initiated net order flows in rival stocks are informative about announcing-firm returns, supporting our conjecture that algorithmic traders have incentives to exploit their informational advantage across stocks. Our analysis also shows that the cross-stock algorithmic trading in the announcers' closer-related firms, business partners, and competitors, respectively, generate significant higher, positive, and negative impacts on the announcing-firms' returns.

Our research is particularly relevant to the cross-stock trading literature (e.g., Caballé and Krishnan, 1994; Tookes, 2008; Jiang et al., 2009; Cao et al., 2015; Pasquariello and Vega, 2015). This line of research suggests that information-based trading may occur in the stocks of rival firms because informed traders have incentives to camouflage any informational advantage or bypass regulatory constraints.[7] The cross-stock trading incentives may also arise due to the reason that firm-specific announcement of one company impacts its product market competitors. Nevertheless, these studies have not addressed the question that which group of traders is more likely to trade across stocks. Our research is the first study highlighting the role of algorithmic traders in generating the cross-stock information linkages during corporate earnings announcements. We also show that the cross-stock algorithmic order flows are more informative when the market capitalizations of announcers are larger than that of rivals and when rival stocks are more liquid than announcing stocks. This is consistent with the notion that algorithmic traders are more willing to trade strategically across stocks when their informational advantage could be better exploited in the rival stocks.

[7] See Tookes (2008) for discussions on insider trading and regulation, and Jiang, McInish, and Upson (2009) for discussions on trading halts.

Overall, our cross-sectional evidence provides further validation of the conjecture on the cross-stock trading incentives of algorithmic traders.

Our study is related to the investor inattention literature that argues that human investors are subject to attention constraints and have limited cognitive capacity in processing large amount of information at once (e.g., Hong et al., 2007; Huang and Liu, 2007; Cohen and Frazzini, 2008; Duffie, 2010; Menzly and Ozbas, 2010; Alldredge and Cicero, 2014; and Cao et al., 2015). We show that algorithmic order flows in rivals become substantially more informative about announcers' returns during the announcing day while human-initiated net order flows remain uninformative, highlighting that algorithmic traders are potentially among the most attentive traders. We also find that the announcing-day algorithmic order flows are only informative when the earnings news is released during trading hours, a scenario when computers have an apparent speed advantage over humans in their capacities of collecting and processing information. Our findings support the notion that the advances in technology reduce the frictions of market monitoring, and that algorithmic traders possess informational advantage in their ability of gathering and processing information more efficiently than human investors (e.g., Biais and Woolley, 2011; Hendershott and Riordan, 2013; Biais et al., 2015). Our analysis highlights the importance of differentiating algorithmic traders from human investors when analyzing investors' delayed response to public information.

Finally, our study is also relevant to regulators' concern on front running orders in correlated securities that is highlighted by SEC (2010) and Angel et al. (2011). One can interpret the results of this paper as algorithmic traders who employ SEC's (2010) directional strategy (more specifically, order anticipation strategies) that anticipate intra-day price movement by exploiting information in customer orders and front running orders in correlated securities, a notion highlighted by Angel et al. (2011). Therefore, our research has important implications for policy makers in designing insider trading legislation and for regulators in maintaining fair and efficient markets.

2. Data

Our proprietary data set comprises all transactions on the Australian cash equity market during the period from October 27, 2008 to October 23, 2009. For each individual trade, the data record the Australian Securities Exchange (ASX) ticker code of the instrument, the date and time to the nearest millisecond, and the price and volume of the trade. A unique feature of this data set is that it identifies whether the buying/selling order(s) that consists of the trade is generated by computer algorithms or human traders.

We also obtain the Order Book data from the Securities Industry Research Centre of Asia-Pacific (SIRCA) for the classification of the trade direction (whether the transaction is buyer-initiated or seller-initiated). This data set contains information on every order that is submitted to the central limit order book, including the order type (order submission, revision, cancellation, or execution), the ASX ticker code of the instrument, the date and time to millisecond precision, the order price and volume, and the order direction (buy or sell order). A unique identification number (ID) is assigned to each new order so that we are able to track the order from its submission through to any revision, cancellation or execution. We classify trades into buyer-initiated and seller-initiated trades based on the order directions of the liquidity demanding (market) orders that initiate the trade. The net order flow is defined as buyer-initiated volume minus seller-initiated volume. We match the Order Book data set to the proprietary transaction level data by the ASX ticker code, the date and time, and the price and volume. This enables us to identify whether liquidity demanding (market) order and liquidity supplying (limit) order(s) that consists of each trade are generated by computers or humans. We classify net order flows as computer-initiated (human-initiated) net order flows if the liquidity demanding (market) orders are generated by computers (humans).

Our study utilizes corporate earnings announcements over the same sample period from SIRCA. Similar to Tookes (2008) and Jiang et al. (2009), we only classify an earnings announcement as valid if there have no other announcements that are released in the same industry within two trading days. Our industry definition follows the Global Industry Classification Standard (GICS) and we include all S&P/ASX 500 stocks within the same "sub-industry" category. For every valid announcement, we match the announcing-firm stock with each of the remaining rival-firm stocks in the same industry. As a result, we obtain 667 announcer-competitor pairs in total.

3. Empirical Results

We estimate cross-stock price impacts of computer- and human-initiated order flows, respectively, to infer the information content of trading in rivals, similar to that of Tookes (2008). The price impact of order flows is of interest because it reflects asymmetric information possessed by traders, and it is typically measured by regressing returns against (signed) order flows (i.e., trade imbalances) (Hasbrouck, 2007). Specifically, our empirical approach is in the spirit of the bivariate vector autoregressive (VAR) model of Hasbrouck (1991):

$$R_t = \alpha + \sum_{i=1}^{N} \beta_i R_{t-i} + \sum_{i=0}^{N} \gamma_i V_{t-i} + \epsilon_t , \quad (1)$$

$$V_t = \kappa + \sum_{i=1}^{N} \delta_i R_{t-i} + \sum_{i=1}^{N} \theta_i V_{t-i} + \nu_t . \quad (2)$$

In Equations (1) and (2), R_t represents the quote return at time t; R_t is defined as natural logarithm of quote midpoint change from time $t-1$ to time t. V_t denotes the net order flows (trade imbalances); the net order flow is calculated as buyer-initiated volume minus seller-initiated volume during the interval between time $t-1$ and time t. Equations (1) and (2) are similar to the standard specification of VAR except that both contemporaneous and lagged net order flows appear in the return equation (Equation (1)), but only lagged returns are included in the net order flow equation (Equation (2)). This is based on the presumption in Hasbrouck (1991) that contemporaneous net order flow can cause quote revisions, but not vice versa.

To consider the cross-stock information linkages, we extend Equations (1) and (2) to multivariate VAR by following Chan et al. (2002) and Tookes (2008). We define R_t as the (2×1) return vector $[R_t^a, R_t^c]'$ where R_t^a and R_t^c denotes quote returns of announcing firms and rival firms, respectively. Similarly, we define V_t as the (2×1) net order flow vector $[V_t^a, V_t^c]'$ where V_t^a and V_t^c denotes trade imbalances in the stocks of announcing firms and rival firms, respectively. Consequently, β_i, γ_i, δ_i, and θ_i represent the (2×2) matrices of coefficients, α and κ refer to (2×1) intercepts vector, and ϵ_t and ν_t are (2×1) vector of disturbance terms. Our extended model can be expressed as a system of four equations:

$$RA_t, RC_t = \alpha + \sum_{i=1}^{6} \beta_i RA_{t-i} + \sum_{i=1}^{6} \beta_{6+i} RC_{t-i} + \sum_{i=0}^{6} \gamma_i VA_{t-i} + \sum_{i=0}^{6} \gamma_{7+i} VC_{t-i} + \epsilon_t \,, \tag{3}$$

$$VA_t, VC_t = \kappa + \sum_{i=1}^{6} \delta_i RA_{t-i} + \sum_{i=1}^{6} \delta_{6+i} RC_{t-i} + \sum_{i=1}^{6} \theta_i VA_{t-i} + \sum_{i=1}^{6} \theta_{6+i} VC_{t-i} + \nu_t \,, \tag{4}$$

where RA_t (RC_t) denotes the quote returns in announcing (rival) firms over the five minute interval t; VA_t (VC_t) denotes the net order flows (trade imbalances) in announcing (rival) firms over the five minute interval t.[8] Consistent with prior studies such as Easley et al.

[8] Chordia and Subrahmanyam (2004) suggest that it is naturally to apply Kyle (1985) model with the signed net order flow over a time interval because the Kyle's (1985) conjecture is that the price changes are related to the pooled net order flow. We follow Easley et al. (1998), Chan et al. (2002), and Tookes (2008) by using five minute interval to calculate signed net order flows. We also repeat our analysis with one minute and ten minute intervals, and the results are qualitatively similar.

(1998), Chan et al. (2002), and Tookes (2008), we use the specification of six lagged returns and order flows to control for transient non-informational effects (Hasbrouck, 1991), lagged adjustment to the information contained in the lagged price change (Chan, 1993), and reversal of price impacts over longer lags (Tookes, 2008).[9] As noted by Pasquariello and Vega (2015), the inclusion of autocorrelations and cross-autocorrelations terms is only likely to weaken our results.

Further, we follow Easley et al. (1998), Chan et al. (2002) and Tookes (2008) standardizing all variables by first extracting its daily mean and then divided by the daily standard deviation for each individual stock. This procedure allows for pooling across stocks so as to increase the empirical test power, and empowers us to assume that the disturbance terms (ϵ_t and ν_t) are homoscedastic. We estimate cross-stock price impacts of net order flows during both benchmark and event periods. Day 0 denotes the event day window when the earnings announcement is released. Similar to Tookes (2008), the benchmark period spans ten trading days around the event day; it includes both the period between day –15 and day –11 and the period between day +11 and day +15. We also include the event window interactions to examine the variation of cross-stock price impact during the periods when the firm-specific earnings announcement has occurred. The event periods consist of five trading days (days –2 to +2) surrounding the announcement. We add a dummy variable (D^w) to indicate the pre-event window (days –2 to –1), event day window (day 0), and post-event window (days +1 to +2), which is equal to one for the corresponding event window and zero otherwise. Finally, in the spirit of Chan et al. (2002) and Tookes (2008), the system of four equations (where the dependent variable is announcer return, competitor return, announcer order flow, and competitor order flow, respectively) is estimated separately by the method of ordinary least square (OLS). Given that our central focus is the impact of information-based

[9] Our results remain largely unchanged when we use more lags (up to ten lags).

trading in rival stocks on announcing-firm returns, we run the following two announcing-firm returns equations (where the dependent variable is the announcer return) with order flows that are initiated by computer algorithms and human brokers, respectively:

$$RA_t = \alpha + \sum_{i=1}^{6} \beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \beta_{i,w} RA_{t-i} D^w + \sum_{i=0}^{6} \gamma_i MVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \gamma_{i,w} MVA_{t-i} D^w + \sum_{i=1}^{6} \delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \delta_{i,w} RC_{t-i} D^w + \sum_{i=0}^{6} \theta_i MVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \theta_{i,w} MVC_{t-i} D^w + \epsilon_t \ , \tag{5}$$

$$RA_t = \alpha + \sum_{i=1}^{6} \beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \beta_{i,w} RA_{t-i} D^w + \sum_{i=0}^{6} \gamma_i HVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \gamma_{i,w} HVA_{t-i} D^w + \sum_{i=1}^{6} \delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \delta_{i,w} RC_{t-i} D^w + \sum_{i=0}^{6} \theta_i HVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \theta_{i,w} HVC_{t-i} D^w + \epsilon_t \ , \tag{6}$$

where MVA_t (MVC_t) denotes the *computer-initiated* net order flows in announcing (rival) firms over the five minute interval t; HVA_t (HVC_t) denotes the *human-initiated* net order flows in announcing (rival) firms over the five minute interval t. For *both* Equations (5) and (6), the dependent variable (RA_t) is the contemporaneous return of the announcing firm, and the independent variables include lagged returns (six lags) in both the announcing firm ($\sum_{i=1}^{6} RA_{t-i}$) and the rival firm ($\sum_{i=1}^{6} RC_{t-i}$). Further, the independent variables in Equation (5) comprise contemporaneous and lagged *computer-initiated* net order flows in both the announcing firm ($\sum_{i=0}^{6} MVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} MVC_{t-i}$); the independent variables in the Equation (6) contain contemporaneous and lagged *human-initiated* net order flows in both the announcing firm ($\sum_{i=0}^{6} HVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} HVC_{t-i}$). The cross-stock price impacts of information-based trading in rival stocks are measured as the sums of the estimated coefficients on rival-firm *computer-* and *human-initiated* order flows, respectively. The alternative hypothesis is that the sums of cross-stock coefficients estimates are significantly different from zero (i.e., $\sum_{i=0}^{6} \theta_i = 0$ for all periods including benchmark period, and $\sum_{i=0}^{i=6} \theta_{i,w} D^w = 0$ for corresponding event windows).

Table I presents descriptive statistics for the volume, trade size, number of trades, and trade price during both benchmark and event periods for announcing firms and competing firms, respectively. All results are presented separately for buyer- and seller-initiated trades. We find that computer-initiated trades overall are more frequent (i.e., larger number of trades) with smaller size compared to human-initiated transactions. This is consistent with notion that the proliferation of modern algorithmic trading is associated with an increasing trend of more frequent transactions and smaller trades (Chordia et al., 2011).

[Insert Table I here]

Table II presents the results for the cross-stock price impacts of *computer*- and *human-initiated* net order flows, respectively. We find that the algorithmic order flows in industry rivals carry information about announcing-firm returns. The sums of the estimated coefficients on computer-initiated net order flows of rival firms are significantly different from zero for all periods (i.e., both the benchmark period and the event windows). In particular, the insignificant pre-event window interactions suggest that the cross-stock information transmission remains largely unchanged during the period immediately before corporate earnings announcements are released. Our pre-event results on computer-initiated trades are consistent with the competitor trading hypothesis of Tookes (2008) in which informed trading is likely to occur in the stocks of rival firms. We do not find any notable cross-stock information linkages that are generated by human-initiated net order flows. Overall, our findings support our conjecture that algorithmic traders facilitate information diffusion across stocks by initiating information-based trades in the stocks of rival firms.

Further, one can also interpret our results as the consequence of the SEC's (2010) directional strategy (more specifically, order anticipation strategies) employed by algorithmic traders who anticipate intra-day price movement by misappropriating customer's order information and front running orders in correlated securities, a notion similar to that of Angel et al. (2011). In addition, although Tookes (2008) and Pasquariello and Vega (2015) suggest that the inclusion of autocorrelations and cross-autocorrelations terms are only likely to work against our results, our findings are robust after the inclusion of these terms to control for transient non-informational effects (Hasbrouck, 1991), lagged adjustment to the recent price changes in rival stocks (Chan, 1993), and any reversal of contemporaneous price impacts over longer lagged order flows (Tookes, 2008; Pasquariello and Vega, 2015).

Next, we notice that the computer-initiated net order flows in rival firms become substantially more informative on the announcing day (i.e., day 0), which is evidenced by the sharp increase in the estimated values of coefficients restrictions (i.e., sums of cross-stock coefficients estimates), and there is no decrease in the information flows from stocks of rival firms to announcing firms during the post-event window. Our announcing-day results are different from that of Tookes' (2008) in which the cross-stock information transmission during the event-day window remains largely unchanged. Our results suggest that the cross-stock information linkages are further enhanced by algorithmic trading during the period in which it is known that the firm-specific earnings news is publically released. Our interpretation is consistent with the attentive informed trading hypothesis of Alldredge and Cicero (2014) in which corporate insiders are most attentive traders about information that is relevant to their firms and become informed by paying close attention to public information. Attentive informed traders gain informational advantage by understanding better about the public announcements on economically related firms compared to outside investors who are relatively inattentive. Our announcing-day results highlight that algorithmic traders are another type of most attentive traders, in addition to the one proposed by Alldredge and Cicero (2014). We argue that algorithmic traders are attentive traders because the use of computers in the process of market monitoring enables algorithmic traders to rapidly react to public information that is relevant to the stocks they trade. Our interpretation of announcing-day results is also similar to that of Kim and Verrecchia (1994), Skinner (1997), and Jin et al. (2012) in which traders' informational advantage immediately after firm-specific news announcements tends to arise from their superior skills in processing public disclosure and in making better judgments about firms' performance. One typical example of attentive algorithmic trading could be the arbitrage strategies in SEC (2010) and Goldstein et al. (2014) that algorithmic traders rapidly capture abnormal price movements among relevant securities upon news releases, which Brogaard et al. (2014) describe as one type of informed trading.

[Insert Table II here]

Firms could be economically linked to one another through many different types of relationships, and past research shows that the corporate news of one firm in particular impact its close competitors or related partners (e.g., Cohen and Frazzini, 2008; Cai et al., 2011). Intuitively, information-based trades should more likely to occur in the closely related rivals than the less relevant ones, because the firm-specific earnings announcements should generate a higher impact on the industry rivals that have closer ties to the announcing firms. For example, Jiang et al. (2009) suggest that the firm-specific news announcements produce higher impact on the rivals that are more correlated to the announcing firms.

We extend the analysis of strategic cross-stock trading by considering both the strength and nature of economic relatedness between the announcer and its industry rival. First, we utilize the historical co-movements of returns and volatilities, respectively, as the proxy for any informational connection that could potentially exist among firms. Specifically, for each earnings announcement, we establish the return (volatility) co-movement by calculating the Pearson correlation between market model residuals (the square of market model residuals) for the announcer stock and each of remaining rival stocks in the same industry. The informational relationships are only accepted for announcer-rival pairs in which the correlation is significant at 10% level. Panel A of Table III presents the results for the selected announcer-rival pairs based on the historical return correlation. Similarly, Panel B of Table III presents the results for the selected announcing-rival pairs based on the historical volatility correlation. We find that algorithmic order flows in the closer competitors of the announcing firms (i.e., any industry rivals significantly co-move with the announcing stocks) generate the higher impacts on the announcers' returns, with stronger results shown in the volatility co-movement group. The sum of cross-stock coefficients estimates on rival-firm *computer-initiated* order flows is 0.0188 (0.0246) for return (volatility) co-movement group while the corresponding value is 0.0168 in Table II. Our findings are similar to that of Akbas et al. (2015) who demonstrate that the strength of the economic relatedness between two firms determines the cross-stock price impacts.

[Insert Table III here]

Second, our study takes into account the nature of informational relatedness based on the measure of idiosyncratic return co-movements in (De Bodt and Roll, 2014). The intuition draws from De Bodt and Roll (2014) who argue that two linked firms in the same industry may not necessarily directly compete with each other. Indeed, the literature highlights various cooperative relationship among industry rivals such as joint ventures or strategic alliances (e.g., Hauswald and Hege, 2003; Cao et al., 2015) and customer-supplier relationships (e.g., Fee and Thomas, 2004; Shahrur, 2005; Ahern and Harford, 2014; Alldredge and Cicero, 2014). We estimate the idiosyncratic return co-movements to distinguish between competing and cooperating industry peers similar to that of De Bodt and Roll (2014). Panel A of Table IV presents the results for stock pairs with positive informational relationships; Panel B of Table IV presents the results for stock pairs with negative informational relationships. We find that algorithmic order flows in business partners (competitors) generate significant positive (negative) cross-stock price impacts. This is consistent with the notion of De Bodt and Roll (2014) that the nature of inter-firm relatedness determines how rivals react to the news of the economically related firm.

[Insert Table IV here]

We further validate our hypotheses of cross-stock algorithmic trading by considering the cross-sectional predictions of Tookes (2008) model in which the cross-stock trading incentives tend to vary with firm-specific characteristics. Panel A of Table V presents the results for announcer-rival pairs where the market capitalization of announcing stock is larger than that of competing stock; Panel B of Table V presents the results for announcer-rival pairs where the market capitalization of announcing stock is smaller than that of competing stock. We find that algorithmic order flows in rivals only generate significant impacts on announcing-firm returns when the market capitalizations of announcing firms are larger than that of rival firms. This is consistent with the cross-sectional implications of Tookes (2008) in which informed traders are more willing to trade in the smaller rival stocks because product market competition implies that these stocks are more vulnerable to the news on economically linked competitors.

Panel A of Table VI presents the results for announcer-rival pairs where the announcing stock is less liquid than the rival stock (the liquidity is measured by average daily turnover of the stocks); Panel B of Table VI presents the results for announcer-rival pairs where the announcing stock is more liquid than the rival stock. We find that cross-stock price impacts generated by algorithmic order flows are only significant when rival stocks are more liquid than announcers. This is consistent with the notion that algorithmic traders tend to initiate trades when the market is deep (Hendershott and Riordan, 2013) and that information-based trading is more likely to occur in liquid stocks that provide better camouflage (Kyle, 1985). Overall, our cross-sectional evidence highlights that algorithmic traders have more incentives to trade across stocks when their informational advantage could be better exploited in the rival stocks.

[Insert Tables V and VI here]

Inspired by the line of research highlighting that abnormal returns reflect unexpected component of information on management earnings forecasts, we separate our sample into two equal-size groups according to the absolute cumulative abnormal return (CAR) of the announcing firms (e.g., Ball and Brown, 1968). For each earnings announcement, we calculate announcers' cumulative abnormal return similar to that of Ball and Brown (1968) for both benchmark and event periods. We divide announcer-rival pairs into two equal-size groups based on the ranking of absolute cumulative abnormal return of announcing stocks. Panel A (Panel B) of Table VII presents the results for the high (low) CAR groups. We find that the computer-initiated net order flows generate significant cross-stock price impacts for the high CAR group (i.e., higher unexpected information), and remain unchanged during the period immediately prior to earnings announcements. Given that the unexpected component of earnings information before the public release tends to be possessed only by informed traders, the results further support our conjecture that algorithmic traders facilitate cross-stock information transmission by initiating information-based trades in rival stocks. Our results also show that the algorithmic order flows are only informative during event-day window for the low CAR group (i.e., less private and less unanticipated information). This is consistent with our conjecture that algorithmic traders are among the most attentive traders who become informed by dynamically monitoring public information that is relevant to the stocks they trade.

[Insert Table VII here]

We validate our hypothesis of attentive algorithmic trading by taking into account whether the earnings announcement is released during or after trading hours. Panel A of

Table VIII presents the results when the announcement is released during trading hours; Panel B of Table VIII presents the results when the announcement is released after trading hours. Intuitively, if earnings announcements occur after hours then there has no difference between computers and humans in the efficiency of responding to information events. Therefore, the announcing-day cross-stock price impacts of algorithmic order flows should mainly exist for the group when earnings news is released during trading hours. This is because the speed advantage differentiates computers from humans in processing and acting on information. Consistent with our conjecture, we find that the announcing-day algorithmic order flows are informative when the earnings news is released during trading hours. We do not observe similar results when the news is announced after hours, a scenario that human investors could be relatively more attentive during the next trading day. Our results again support the notion that algorithmic traders are attentive traders who become informed by paying close attention to public information and by speedily reacting to information.

[Insert Table VIII here]

We further extend our analysis of cross-stock price impacts of net order flows by considering whether computers or humans demand or supply liquidity. We are inspired by the line of emerging research on algorithmic trading that break down net order flow (i.e., buyer-initiated transaction minus seller-initiated transaction) into four possible categories: computer (take liquidity) and computer (make liquidity), computer (take liquidity) and human (make liquidity), human (take liquidity) and computer (make liquidity), human (take liquidity) and human (make liquidity) (e.g., Brogaard et al., 2014; Chaboud et al., 2014). Consistent with our prior results on computer-initiated net order flows, we find algorithmic trading facilitates information diffusion across stocks when computer demand liquidity from computers or humans. Our findings are consistent with the view that algorithmic trading improves informational efficiency through liquidty demanding orders (Brogaard et al., 2014; Chaboud et al., 2014). We also find that there has significant increase in cross-stock information transmission when computers take liquidity from humans during event-day window. This is consistent with the event arbitrage strategies in SEC (2010) that algorithmic traders speedily capture the inefficiencies via liquidity demanding orders, imposing adverse selection costs to slow traders (Brogaard et al., 2014; Chaboud et al., 2014). In addition, humans seem to trade in the wrong direction when demand liquidity from computers. This is consistent with the finding in Chaboud et al. (2014) that the liquidity supplying orders of algorithmic traders reflect information more quickly.

[Insert Table IX here]

We perform two sets of robustness tests. First, the commonality in liquidity literature such as Chordia et al. (2000) and Hasbrouck and Seppi (2001) suggest that market-wide effects may cause correlated returns and volumes. We include quote returns of All Ordinaries Index into the regression analysis (Table X) and our results remain unchanged.[10] Second, instead of five minute interval utilized throughout the analysis, we use both ten minute interval and one minute interval to calculate net order flows. Table XI reports the results obtained with ten minute interval. We find both our results in Table XI with ten minute interval and in unreported analysis with one minute interval are robust to using alternative time length to calculate net order flows.

[Insert Tables X and XI here]

4. Conclusions

This paper investigates the role of algorithmic trading in generating cross-stock information linkages during the periods around corporate earnings announcements. We find that

[10] The All Ordinaries Index is one of the most important market indicators and comprise the 500 largest stocks in Australia.

computer-initiated net order flows in rival stocks have information content for announcing-firm returns. Our results highlight that algorithmic traders have incentives to exploit their informational advantage across stocks by initiating information-based trades in the stocks of rival firms. We also demonstrate that the cross-stock algorithmic trading in the announcers' closer-related firms, business partners, and competitors, respectively, generate significant higher, positive, and negative impacts on the announcing-firms' returns. This suggests the strength and the nature of the informational relatedness between announcers and rivals determines the degree and direction of the cross-stock price impacts, respectively. Further, our findings indicate that the cross-stock algorithmic trading is more likely to occur when announcing firms are larger than rivals and when rival firms are more liquid than announcers. This is consistent with the notion that algorithmic traders are more willing to trade strategically across stocks when their informational advantage could be better exploited in the rival stocks.

Our results that cross-stock algorithmic order flows become substantially more informative during the announcing day highlights that algorithmic traders are potentially among the most attentive traders. Consistent with the conjecture that computers differentiate from humans in the terms of the information collecting and processing capacities, we also find that the announcing-day algorithmic order flows are only informative when the earnings news is released during trading hours. Our findings support the notion that the advances in technology reduce the frictions of market monitoring, and that algorithmic traders possess informational advantage in their ability of gathering and processing information more efficiently than human investors. Overall, our findings highlight that the proliferation of algorithmic trading plays a beneficial role in the price discovery process by facilitating cross-stock transmission of information into prices.

Finally, our study is also relevant to regulators' concern on front running orders in correlated securities that is highlighted by SEC (2010) and Angel et al. (2011). One can interpret our results as algorithmic traders anticipate intra-day price movement by exploiting information in customer orders and front running orders in the related stocks. Therefore, our research has important implications for policy makers in designing insider trading legislation and for regulators in maintaining fair and efficient markets.

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Table I. Descriptive statistics

This table presents descriptive statistics for the volume, trade size, number of trades, and trade price during both benchmark and event periods for the stocks of announcing firms and rival firms, respectively. All results are presented separately for buyer- and seller-initiated trades.

Panel A: Computer-initiated trades in the stocks of announcing firms

	Buyer-Initiated Trades				*Seller-Initiated Trades*			
	Mean	Median	Min.	Max.	Mean	Median	Min.	Max.
Volume (000)	862	176	2	16,099	809	163	3	15,619
Volume (small) (000)	33	20	0	224	30	12	0	229
Volume (medium) (000)	307	113	2	3,113	277	97	3	3,054
Volume (large) (000)	645	84	10	13,797	624	79	10	14,207
Trade Size	3,508	1,454	111	28,240	4,138	1,345	96	56,326
No. of Trades	399	207	1	3,057	363	151	1	3,081
No. of Trades (small)	236	123	0	1,769	219	95	0	1,749
No. of Trades (medium)	147	60	1	1,437	131	46	1	1,440
No. of Trades (large)	16	2	0	288	13	2	0	178
Trade Price	6.60	2.45	0.14	57.35	6.65	2.44	0.14	57.35

Panel B: Computer-initiated trades in the stocks of rival firms

	Buyer-Initiated Trades				*Seller-Initiated Trades*			
	Mean	Median	Min.	Max.	Mean	Median	Min.	Max.
Volume (000)	846	223	2	13,258	795	216	3	14,387
Volume (small) (000)	23	9	0	283	21	8	0	246
Volume (medium) (000)	235	74	2	2,994	227	72	2	2,843
Volume (large) (000)	650	106	10	12,556	619	105	10	13,007
Trade Size	6,248	2,101	92	108,546	6,849	2,293	94	115,995
No. of Trades	291	135	2	3,503	268	105	3	3,291
No. of Trades (small)	169	61	0	2,003	153	51	0	1,852
No. of Trades (medium)	107	40	0	1,447	101	36	0	1,388
No. of Trades (large)	15	3	0	238	14	3	0	294
Trade Price	4.36	1.59	0.07	57.62	4.35	1.58	0.07	57.60

Panel C: Human-initiated trades in the stocks of announcing firms

	Buyer-Initiated Trades				*Seller-Initiated Trades*			
	Mean	Median	Min.	Max.	Mean	Median	Min.	Max.
Volume (000)	399	69	1	8,721	364	83	1	8,935
Volume (small) (000)	3	1	0	37	3	1	0	31
Volume (medium) (000)	68	27	1	673	62	29	1	690
Volume (large) (000)	411	63	10	8,335	366	64	10	8,772
Trade Size	8,393	3,382	151	61,672	9,605	3,749	241	75,173
No. of Trades	51	17	1	455	43	17	1	422
No. of Trades (small)	17	3	0	181	14	3	0	137
No. of Trades (medium)	26	10	1	256	23	11	0	255
No. of Trades (large)	7	2	0	110	6	2	0	76
Trade Price	6.64	2.42	0.14	57.34	6.74	2.47	0.14	57.38

Panel D: Human-initiated trades in the stocks of rival firms

	Buyer-Initiated Trades				*Seller-Initiated Trades*			
	Mean	Median	Min.	Max.	Mean	Median	Min.	Max.
Volume (000)	473	98	1	8,451	423	104	1	8,002
Volume (small) (000)	2	1	0	39	2	1	0	28
Volume (medium) (000)	57	25	1	647	54	24	1	694
Volume (large) (000)	492	101	10	8,294	417	89	10	7,657
Trade Size	13,232	5,533	275	131,021	14,029	5,843	242	126,822
No. of Trades	38	16	1	538	34	16	1	482
No. of Trades (small)	10	2	0	240	8	1	0	174
No. of Trades (medium)	20	7	0	274	19	7	0	288
No. of Trades (large)	8	2	0	109	7	2	0	122
Trade Price	4.39	1.59	0.07	57.65	4.44	1.70	0.07	57.61

Table II. The cross-stock price impacts of information-based trading in industry rivals of announcing firms

This table presents the estimated cross-stock price impacts of algorithmic and non-algorithmic order flows, respectively, to infer the information content of trading activities that occur across stocks in the stocks of industry rivals. The "price impact" refers to the impact of information-based trading in rival stocks on the prices of announcing firms. We run the following two regression models of Equations (5) and (6) to estimate cross-stock price impacts of order flows that are initiated by computer algorithms and human brokers, respectively:

$$RA_t = \alpha + \sum_{i=1}^{6}\beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3}\beta_{i,w} RA_{t-i}D^w + \sum_{i=0}^{6}\gamma_i MVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3}\gamma_{i,w} MVA_{t-i}D^w + \sum_{i=1}^{6}\delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3}\delta_{i,w} RC_{t-i}D^w + \sum_{i=0}^{6}\theta_i MVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3}\theta_{i,w} MVC_{t-i}D^w + \epsilon_t ,$$

$$RA_t = \alpha + \sum_{i=1}^{6}\beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3}\beta_{i,w} RA_{t-i}D^w + \sum_{i=0}^{6}\gamma_i HVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3}\gamma_{i,w} HVA_{t-i}D^w + \sum_{i=1}^{6}\delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3}\delta_{i,w} RC_{t-i}D^w + \sum_{i=0}^{6}\theta_i HVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3}\theta_{i,w} HVC_{t-i}D^w + \epsilon_t .$$

RA_t (RC_t) denotes the quote returns in announcing (rival) firms over the five minute interval t. The quote return is defined as the natural logarithm of quote midpoint change during the five minute interval t. MVA_t (MVC_t) denotes the *computer-initiated* net order flows (trade imbalances) in announcing (rival) firms over the five minute interval t; HVA_t (HVC_t) denotes the *human-initiated* net order flows (trade imbalances) in announcing (rival) firms over the five minute interval t. The net order flow is calculated as buyer-initiated volume minus seller-initiated volume during the five minute interval t. For *both* equations, the dependent variable (RA_t) is the contemporaneous return of the announcing firm, and the independent variables include lagged returns (six lags) in both the announcing firm ($\sum_{i=1}^{6} RA_{t-i}$) and the rival firm ($\sum_{i=1}^{6} RC_{t-i}$). The independent variables in the *first* equation also contain contemporaneous and lagged *computer-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} MVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} MVC_{t-i}$). The independent variables in the *second* equation also contain contemporaneous and lagged *human-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} HVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} HVC_{t-i}$). For each individual stock, all variables are standardized by first subtracting its daily mean and then dividing by its daily standard deviation. This procedure allows for pooling across stocks so as to increase the empirical test power. We estimate cross-stock price impacts of algorithmic and non-algorithmic order flows, respectively, during both benchmark and event periods. We define day 0 as the event day when the earnings announcement is released. The benchmark period spans ten trading days surrounding the event day, which includes both the period between day –15 and day –11 and the period between day +11 and day +15. The event period consist of five days (days –2 to +2) around the earnings announcement. D^w is a dummy variable indicating the pre-event window (days –2 to –1), event day window (day 0), and post-event window (days +1 to +2); D^w is equal to one for the corresponding event window and zero otherwise. The cross-stock price impacts are measured as the sums of the estimated coefficients on rival-firm algorithmic and non-algorithmic order flows, respectively. The null hypothesis is that the sums of cross-stock coefficients estimates are not significantly different from zero (i.e., $\sum_{i=0}^{6}\theta_i = 0$ for all periods and $\sum_{i=0}^{i=6}\theta_{i,w}D^w = 0$ for event windows). The estimated values of coefficients restrictions (i.e., sums of cross-stock coefficients estimates) are presented; the corresponding *p*-values are reported in parentheses below the estimates. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: Announcing-Firm Return (RA_t)				
Explanatory Variables	All Periods	Pre-Event Interaction	Event Day Interaction	Post-Event Interaction
Order Flows Initiated by Computer Algorithms				
Rival-Firm Returns	0.0276***	-0.0102	0.0001	-0.0295
	(0.0007)	(0.6129)	(0.9967)	(0.1323)
Rival-Firm Order Flows	0.0168**	-0.0076	0.0568**	-0.0283
	(0.0257)	(0.6766)	(0.0208)	(0.1210)
Order Flows Initiated by Human Brokers				
Rival-Firm Returns	0.0329***	-0.0202	0.0154	-0.0284
	(0.0001)	(0.3230)	(0.5671)	(0.1572)
Rival-Firm Order Flows	0.0164	-0.0219	-0.0477	-0.0084
	(0.1479)	(0.4104)	(0.1780)	(0.7591)

Table III. The cross-stock price impacts of information-based trading in informationally related firms

This table presents the estimated cross-stock price impacts of information-based trading in informationally related firms. We use the historical co-movements of returns and volatilities, respectively, as the proxy for any informational relationships that could potentially exist among firms. For each valid earnings announcement, we establish the return (volatility) co-movement by calculating the Pearson correlation between market model residuals (the square of market model residuals) for the announcer stock and each of remaining rival stocks in the same industry. The informational relationships are only accepted when the correlation is significant at 10% level. Panel A of Table III presents the results for the selected announcer-rival pairs based on the historical return correlation. Similarly, Panel B of Table III presents the results for the selected announcing-rival pairs based on the historical volatility correlation. Specifically, for both Panel A and B, we run the following two regression models of Equations (5) and (6) to estimate cross-stock price impacts of order flows that are initiated by computer algorithms and human brokers, respectively:

$$RA_t = \alpha + \sum_{i=1}^{6}\beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3}\beta_{i,w} RA_{t-i}D^w + \sum_{i=0}^{6}\gamma_i MVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3}\gamma_{i,w} MVA_{t-i}D^w + \sum_{i=1}^{6}\delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3}\delta_{i,w} RC_{t-i}D^w + \sum_{i=0}^{6}\theta_i MVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3}\theta_{i,w} MVC_{t-i}D^w + \epsilon_t \ ,$$

$$RA_t = \alpha + \sum_{i=1}^{6}\beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3}\beta_{i,w} RA_{t-i}D^w + \sum_{i=0}^{6}\gamma_i HVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3}\gamma_{i,w} HVA_{t-i}D^w + \sum_{i=1}^{6}\delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3}\delta_{i,w} RC_{t-i}D^w + \sum_{i=0}^{6}\theta_i HVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3}\theta_{i,w} HVC_{t-i}D^w + \epsilon_t \ .$$

RA_t (RC_t) denotes the quote returns in announcing (rival) firms over the five minute interval t. The quote return is defined as the natural logarithm of quote midpoint change during the five minute interval t. MVA_t (MVC_t) denotes the *computer-initiated* net order flows (trade imbalances) in announcing (rival) firms over the five minute interval t; HVA_t (HVC_t) denotes the *human-initiated* net order flows (trade imbalances) in announcing (rival) firms over the five minute interval t. The net order flow is calculated as buyer-initiated volume minus seller-initiated volume during the five minute interval t. For *both* equations, the dependent variable (RA_t) is the contemporaneous return of the announcing firm, and the independent variables include lagged returns (six lags) in both the announcing firm ($\sum_{i=1}^{6} RA_{t-i}$) and the rival firm ($\sum_{i=1}^{6} RC_{t-i}$). The independent variables in the *first* equation also contain contemporaneous and lagged *computer-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} MVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} MVC_{t-i}$). The independent variables in the *second* equation also contain contemporaneous and lagged *human-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} HVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} HVC_{t-i}$). For each individual stock, all variables are standardized by first subtracting its daily mean and then dividing by its daily standard deviation. This procedure allows for pooling across stocks so as to increase the empirical test power. We estimate cross-stock price impacts of algorithmic and non-algorithmic order flows, respectively, during both benchmark and event periods. We define day 0 as the event day when the earnings announcement is released. The benchmark period spans ten trading days surrounding the event day, which includes both the period between day –15 and day –11 and the period between day +11 and day +15. The event period consist of five days (days –2 to +2) around the earnings announcement. D^w is a dummy variable indicating the pre-event window (days –2 to –1), event day window (day 0), and post-event window (days +1 to +2); D^w is equal to one for the corresponding event window and zero otherwise. The cross-stock price impacts are measured as the sums of the estimated coefficients on rival-firm algorithmic and non-algorithmic order flows, respectively. The null hypothesis is that the sums of cross-stock coefficients estimates are not significantly different from zero (i.e., $\sum_{i=0}^{6}\theta_i = 0$ for all periods and $\sum_{i=0}^{i=6}\theta_{i,w}D^w = 0$ for event windows). The estimated values of coefficients restrictions (i.e., sums of cross-stock coefficients estimates) are presented; the corresponding *p*-values are reported in parentheses below the estimates.

Panel A: Informational relationship based on historical return co-movement

Dependent Variable: Announcing-Firm Return (RA_t)				
Explanatory Variables	All Periods	Pre-Event Interaction	Event Day Interaction	Post-Event Interaction
Order Flows Initiated by Computer Algorithms				
Rival-Firm Returns	0.0333***	-0.0090	-0.0246	-0.0239
	(0.0003)	(0.6921)	(0.4091)	(0.2805)
Rival-Firm Order Flows	0.0188**	-0.0180	0.0719***	-0.0306
	(0.0238)	(0.3695)	(0.0092)	(0.1350)
Order Flows Initiated by Human Brokers				
Rival-Firm Returns	0.0391***	-0.0315	-0.0180	-0.0245
	(0.0000)	(0.1743)	(0.5537)	(0.2801)
Rival-Firm Order Flows	0.0181	-0.0053	-0.0189	-0.0019
	(0.1407)	(0.8560)	(0.6382)	(0.9502)

Panel B: Informational relationship based on historical volatility co-movement

Dependent Variable: Announcing-Firm Return (RA_t)				
Explanatory Variables	All Periods	Pre-Event Interaction	Event Day Interaction	Post-Event Interaction
Order Flows Initiated by Computer Algorithms				
Rival-Firm Returns	0.0373***	-0.0155	-0.0161	-0.0146
	(0.0003)	(0.5505)	(0.6354)	(0.5658)
Rival-Firm Order Flows	0.0246***	-0.0268	0.0956***	-0.0183
	(0.0085)	(0.2374)	(0.0018)	(0.4234)
Order Flows Initiated by Human Brokers				
Rival-Firm Returns	0.0506***	-0.0400	0.0100	-0.0221
	(0.0000)	(0.1285)	(0.7738)	(0.3934)
Rival-Firm Order Flows	0.0227*	-0.0119	-0.0354	0.0005
	(0.0965)	(0.7143)	(0.4209)	(0.9888)

Table IV. The cross-stock price impacts of information-based trading in business partners versus competitors

This table presents the estimated cross-stock price impacts of information-based trading in business partners and competitors, respectively. We estimate the idiosyncratic return co-movements to distinguish between competing and cooperating industry peers. Panel A of Table IV presents the results for stock pairs with positive informational relationships; Panel B of Table IV presents the results for stock pairs with negative informational relationships. Specifically, for both Panel A and B, we run the following two regression models of Equations (5) and (6) to estimate cross-stock price impacts of order flows that are initiated by computer algorithms and human brokers, respectively:

$$RA_t = \alpha + \sum_{i=1}^{6} \beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \beta_{i,w} RA_{t-i} D^w + \sum_{i=0}^{6} \gamma_i MVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \gamma_{i,w} MVA_{t-i} D^w + \sum_{i=1}^{6} \delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \delta_{i,w} RC_{t-i} D^w + \sum_{i=0}^{6} \theta_i MVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \theta_{i,w} MVC_{t-i} D^w + \epsilon_t \ ,$$

$$RA_t = \alpha + \sum_{i=1}^{6} \beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \beta_{i,w} RA_{t-i} D^w + \sum_{i=0}^{6} \gamma_i HVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \gamma_{i,w} HVA_{t-i} D^w + \sum_{i=1}^{6} \delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \delta_{i,w} RC_{t-i} D^w + \sum_{i=0}^{6} \theta_i HVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \theta_{i,w} HVC_{t-i} D^w + \epsilon_t \ .$$

RA_t (RC_t) denotes the quote returns in announcing (rival) firms over the five minute interval t. The quote return is defined as the natural logarithm of quote midpoint change during the five minute interval t. MVA_t (MVC_t) denotes the *computer-initiated* net order flows (trade imbalances) in announcing (rival) firms over the five minute interval t; HVA_t (HVC_t) denotes the *human-initiated* net order flows (trade imbalances) in announcing (rival) firms over the five minute interval t. The net order flow is calculated as buyer-initiated volume minus seller-initiated volume during the five minute interval t. For *both* equations, the dependent variable (RA_t) is the contemporaneous return of the announcing firm, and the independent variables include lagged returns (six lags) in both the announcing firm ($\sum_{i=1}^{6} RA_{t-i}$) and the rival firm ($\sum_{i=1}^{6} RC_{t-i}$). The independent variables in the *first* equation also contain contemporaneous and lagged *computer-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} MVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} MVC_{t-i}$). The independent variables in the *second* equation also contain contemporaneous and lagged *human-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} HVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} HVC_{t-i}$). For each individual stock, all variables are standardized by first subtracting its daily mean and then dividing by its daily standard deviation. This procedure allows for pooling across stocks so as to increase the empirical test power. We estimate cross-stock price impacts of algorithmic and non-algorithmic order flows, respectively, during both benchmark and event periods. We define day 0 as the event day when the earnings announcement is released. The benchmark period spans ten trading days surrounding the event day, which includes both the period between day –15 and day –11 and the period between day +11 and day +15. The event period consist of five days (days –2 to +2) around the earnings announcement. D^w is a dummy variable indicating the pre-event window (days –2 to –1), event day window (day 0), and post-event window (days +1 to +2); D^w is equal to one for the corresponding event window and zero otherwise. The cross-stock price impacts are measured as the sums of the estimated coefficients on rival-firm algorithmic and non-algorithmic order flows, respectively. The null hypothesis is that the sums of cross-stock coefficients estimates are not significantly different from zero (i.e., $\sum_{i=0}^{6} \theta_i = 0$ for all periods and $\sum_{i=0}^{i=6} \theta_{i,w} D^w = 0$ for event windows). The estimated values of coefficients restrictions (i.e., sums of cross-stock coefficients estimates) are presented; the corresponding *p*-values are reported in parentheses below the estimates.

Panel A: Cross-stock trading in business partners

Dependent Variable: Announcing-Firm Return (RA_t)				
Explanatory Variables	All Periods	Pre-Event Interaction	Event Day Interaction	Post-Event Interaction
Order Flows Initiated by Computer Algorithms				
Rival-Firm Returns	0.0334***	-0.0064	-0.0258	-0.0282
	(0.0003)	(0.7796)	(0.3889)	(0.2060)
Rival-Firm Order Flows	0.0202**	-0.0205	0.0702**	-0.0304
	(0.0159)	(0.3075)	(0.0112)	(0.1388)
Order Flows Initiated by Human Brokers				
Rival-Firm Returns	0.0396***	-0.0281	-0.0213	-0.0275
	(0.0000)	(0.2277)	(0.4867)	(0.2287)
Rival-Firm Order Flows	0.0201	-0.0105	-0.0180	-0.0037
	(0.1032)	(0.7195)	(0.6565)	(0.9039)

Panel B: Cross-stock trading in competitors

Dependent Variable: Announcing-Firm Return (RA_t)				
Explanatory Variables	All Periods	Pre-Event Interaction	Event Day Interaction	Post-Event Interaction
Order Flows Initiated by Computer Algorithms				
Rival-Firm Returns	0.1056	-0.7553**	-0.5343	0.1704
	(0.4041)	(0.0357)	(0.2462)	(0.4782)
Rival-Firm Order Flows	-0.2728**	0.5684*	0.4679	0.2183
	(0.0300)	(0.0751)	(0.2838)	(0.6439)
Order Flows Initiated by Human Brokers				
Rival-Firm Returns	0.0264	-0.5931	-0.4994	0.3520
	(0.8235)	(0.1444)	(0.9221)	(0.1257)
Rival-Firm Order Flows	-0.3015*	0.9078*	-1.3189	0.3120
	(0.0649)	(0.0622)	(0.8693)	(0.4903)

Table V. Relative size and cross-stock price impacts of information-based trading in rivals

This table presents the variation of cross-stock price impacts of order flows based on relative market share. We dividing our sample based on relative market shares. Panel A of Table V presents the results for announcer-rival pairs where the market capitalization of announcing stock is larger than that of competing stock; Panel B of Table V presents the results for announcer-rival pairs where the market capitalization of announcing stock is smaller than that of competing stock. Specifically, for both Panel A and B, we run the following two regression models of Equations (5) and (6) to estimate cross-stock price impacts of order flows that are initiated by computer algorithms and human brokers, respectively:

$$RA_t = \alpha + \sum_{i=1}^{6} \beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \beta_{i,w} RA_{t-i} D^w + \sum_{i=0}^{6} \gamma_i MVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \gamma_{i,w} MVA_{t-i} D^w + \sum_{i=1}^{6} \delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \delta_{i,w} RC_{t-i} D^w + \sum_{i=0}^{6} \theta_i MVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \theta_{i,w} MVC_{t-i} D^w + \epsilon_t \ ,$$

$$RA_t = \alpha + \sum_{i=1}^{6} \beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \beta_{i,w} RA_{t-i} D^w + \sum_{i=0}^{6} \gamma_i HVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \gamma_{i,w} HVA_{t-i} D^w + \sum_{i=1}^{6} \delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \delta_{i,w} RC_{t-i} D^w + \sum_{i=0}^{6} \theta_i HVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \theta_{i,w} HVC_{t-i} D^w + \epsilon_t \ .$$

RA_t (RC_t) denotes the quote returns in announcing (rival) firms over the five minute interval t. The quote return is defined as the natural logarithm of quote midpoint change during the five minute interval t. MVA_t (MVC_t) denotes the *computer-initiated* net order flows (trade imbalances) in announcing (rival) firms over the five minute interval t; HVA_t (HVC_t) denotes the *human-initiated* net order flows (trade imbalances) in announcing (rival) firms over the five minute interval t. The net order flow is calculated as buyer-initiated volume minus seller-initiated volume during the five minute interval t. For *both* equations, the dependent variable (RA_t) is the contemporaneous return of the announcing firm, and the independent variables include lagged returns (six lags) in both the announcing firm ($\sum_{i=1}^{6} RA_{t-i}$) and the rival firm ($\sum_{i=1}^{6} RC_{t-i}$). The independent variables in the *first* equation also contain contemporaneous and lagged *computer-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} MVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} MVC_{t-i}$). The independent variables in the *second* equation also contain contemporaneous and lagged *human-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} HVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} HVC_{t-i}$). For each individual stock, all variables are standardized by first subtracting its daily mean and then dividing by its daily standard deviation. This procedure allows for pooling across stocks so as to increase the empirical test power. We estimate cross-stock price impacts of algorithmic and non-algorithmic order flows, respectively, during both benchmark and event periods. We define day 0 as the event day when the earnings announcement is released. The benchmark period spans ten trading days surrounding the event day, which includes both the period between day –15 and day –11 and the period between day +11 and day +15. The event period consist of five days (days –2 to +2) around the earnings announcement. D^w is a dummy variable indicating the pre-event window (days –2 to –1), event day window (day 0), and post-event window (days +1 to +2); D^w is equal to one for the corresponding event window and zero otherwise. The cross-stock price impacts are measured as the sums of the estimated coefficients on rival-firm algorithmic and non-algorithmic order flows, respectively. The null hypothesis is that the sums of cross-stock coefficients estimates are not significantly different from zero (i.e., $\sum_{i=0}^{6} \theta_i = 0$ for all periods and $\sum_{i=0}^{i=6} \theta_{i,w} D^w = 0$ for event windows). The estimated values of coefficients restrictions (i.e., sums of cross-stock coefficients estimates) are presented; the corresponding *p*-values are reported in parentheses below the estimates.

Panel A: Large announcing firms versus small rival firms

Dependent Variable: Announcing-Firm Return (RA_t)				
Explanatory Variables	All Periods	Pre-Event Interaction	Event Day Interaction	Post-Event Interaction
Order Flows Initiated by Computer Algorithms				
Rival-Firm Returns	0.0325***	-0.0351	-0.0433	-0.0155
	(0.0017)	(0.1690)	(0.2045)	(0.5463)
Rival-Firm Order Flows	0.0185*	-0.0018	0.0713**	-0.0741***
	(0.0577)	(0.9388)	(0.0301)	(0.0024)
Order Flows Initiated by Human Brokers				
Rival-Firm Returns	0.0435***	-0.0452*	-0.0060	-0.0302
	(0.0000)	(0.0810)	(0.8622)	(0.2481)
Rival-Firm Order Flows	-0.0059	-0.0123	-0.0976*	-0.0032
	(0.7092)	(0.7430)	(0.0574)	(0.9374)

Panel B: Small announcing firms versus large rival firms

Dependent Variable: Announcing-Firm Return (RA_t)				
Explanatory Variables	All Periods	Pre-Event Interaction	Event Day Interaction	Post-Event Interaction
Order Flows Initiated by Computer Algorithms				
Rival-Firm Returns	0.0200	0.0311	0.0581	-0.0477
	(0.1310)	(0.3439)	(0.1610)	(0.1191)
Rival-Firm Order Flows	0.0147	-0.0181	0.0416	0.0248
	(0.2141)	(0.5286)	(0.2624)	(0.3690)
Order Flows Initiated by Human Brokers				
Rival-Firm Returns	0.0171	0.0155	0.0527	-0.0252
	(0.2023)	(0.6399)	(0.2127)	(0.4219)
Rival-Firm Order Flows	0.0391**	-0.0362	-0.0119	-0.0148
	(0.0163)	(0.3406)	(0.8088)	(0.6953)

Table VI. Relative liquidity and cross-stock price impacts of information-based trading in rivals

This table presents the variation of cross-stock price impacts of order flows based on relative liquidity. We divide our sample based on the relative liquidity. Panel A of Table VI presents the results for announcer-rival pairs where the announcer is less liquid than rival; Panel B of Table VI presents the results for announcer-rival pairs where the announcer is more liquid than rival. The liquidity is measured by average daily turnover of the stocks. Specifically, for both Panel A and B, we run the following two regression models of Equations (5) and (6) to estimate cross-stock price impacts of order flows that are initiated by computer algorithms and human brokers, respectively:

$$RA_t = \alpha + \sum_{i=1}^{6} \beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \beta_{i,w} RA_{t-i} D^w + \sum_{i=0}^{6} \gamma_i MVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \gamma_{i,w} MVA_{t-i} D^w + \sum_{i=1}^{6} \delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \delta_{i,w} RC_{t-i} D^w + \sum_{i=0}^{6} \theta_i MVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \theta_{i,w} MVC_{t-i} D^w + \epsilon_t \ ,$$

$$RA_t = \alpha + \sum_{i=1}^{6} \beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \beta_{i,w} RA_{t-i} D^w + \sum_{i=0}^{6} \gamma_i HVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \gamma_{i,w} HVA_{t-i} D^w + \sum_{i=1}^{6} \delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \delta_{i,w} RC_{t-i} D^w + \sum_{i=0}^{6} \theta_i HVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \theta_{i,w} HVC_{t-i} D^w + \epsilon_t \ .$$

RA_t (RC_t) denotes the quote returns in announcing (rival) firms over the five minute interval t. The quote return is defined as the natural logarithm of quote midpoint change during the five minute interval t. MVA_t (MVC_t) denotes the *computer-initiated* net order flows (trade imbalances) in announcing (rival) firms over the five minute interval t; HVA_t (HVC_t) denotes the *human-initiated* net order flows (trade imbalances) in announcing (rival) firms over the five minute interval t. The net order flow is calculated as buyer-initiated volume minus seller-initiated volume during the five minute interval t. For *both* equations, the dependent variable (RA_t) is the contemporaneous return of the announcing firm, and the independent variables include lagged returns (six lags) in both the announcing firm ($\sum_{i=1}^{6} RA_{t-i}$) and the rival firm ($\sum_{i=1}^{6} RC_{t-i}$). The independent variables in the *first* equation also contain contemporaneous and lagged *computer-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} MVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} MVC_{t-i}$). The independent variables in the *second* equation also contain contemporaneous and lagged *human-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} HVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} HVC_{t-i}$). For each individual stock, all variables are standardized by first subtracting its daily mean and then dividing by its daily standard deviation. This procedure allows for pooling across stocks so as to increase the empirical test power. We estimate cross-stock price impacts of algorithmic and non-algorithmic order flows, respectively, during both benchmark and event periods. We define day 0 as the event day when the earnings announcement is released. The benchmark period spans ten trading days surrounding the event day, which includes both the period between day –15 and day –11 and the period between day +11 and day +15. The event period consist of five days (days –2 to +2) around the earnings announcement. D^w is a dummy variable indicating the pre-event window (days –2 to –1), event day window (day 0), and post-event window (days +1 to +2); D^w is equal to one for the corresponding event window and zero otherwise. The cross-stock price impacts are measured as the sums of the estimated coefficients on rival-firm algorithmic and non-algorithmic order flows, respectively. The null hypothesis is that the sums of cross-stock coefficients estimates are not significantly different from zero (i.e., $\sum_{i=0}^{6} \theta_i = 0$ for all periods and $\sum_{i=0}^{i=6} \theta_{i,w} D^w = 0$ for event windows). The estimated values of coefficients restrictions (i.e., sums of cross-stock coefficients estimates) are presented; the corresponding *p*-values are reported in parentheses below the estimates.

Panel A: Less liquid announcers versus more liquid rivals

Dependent Variable: Announcing-Firm Return (RA_t)				
Explanatory Variables	All Periods	Pre-Event Interaction	Event Day Interaction	Post-Event Interaction
Order Flows Initiated by Computer Algorithms				
Rival-Firm Returns	0.0228**	0.0075	0.0106	-0.0170
	(0.0482)	(0.7929)	(0.7749)	(0.5276)
Rival-Firm Order Flows	0.0188*	-0.0056	0.0780**	-0.0388
	(0.0684)	(0.8221)	(0.0227)	(0.1132)
Order Flows Initiated by Human Brokers				
Rival-Firm Returns	0.0261**	0.0168	0.0373	-0.0345
	(0.0248)	(0.5571)	(0.3237)	(0.2104)
Rival-Firm Order Flows	0.0274*	-0.0531	-0.1087**	0.0132
	(0.0683)	(0.1339)	(0.0219)	(0.7184)

Panel B: More liquid announcers versus less liquid rivals

Dependent Variable: Announcing-Firm Return (RA_t)				
Explanatory Variables	All Periods	Pre-Event Interaction	Event Day Interaction	Post-Event Interaction
Order Flows Initiated by Computer Algorithms				
Rival-Firm Returns	0.0326***	-0.0295	-0.0099	-0.0449
	(0.0047)	(0.3011)	(0.7917)	(0.1189)
Rival-Firm Order Flows	0.0155	-0.0108	0.0326	-0.0139
	(0.1595)	(0.6844)	(0.3562)	(0.6119)
Order Flows Initiated by Human Brokers				
Rival-Firm Returns	0.0394***	-0.0585**	-0.0036	-0.0188
	(0.0007)	(0.0447)	(0.9256)	(0.5242)
Rival-Firm Order Flows	0.0020	0.0173	0.0366	-0.0403
	(0.9063)	(0.6683)	(0.4953)	(0.3365)

Table VII. Cumulative abnormal return and cross-stock price impacts of information-based trading in rivals

This table presents the impact of information content of earnings announcements on cross-stock price impacts of algorithmic and non-algorithmic order flows, respectively. We separate our sample in half according to the absolute cumulative abnormal return (CAR). For each earnings announcement, we calculate cumulative abnormal return for both benchmark and event periods. We divide announcer-rival pairs into two separate groups based on the ranking of absolute cumulative abnormal return of announcing stocks. Panel A (Panel B) of Table VII presents the results for stock pairs with higher (lower) absolute cumulative abnormal return. Specifically, for both Panel A and B, we run the following two regression models of Equations (5) and (6) to estimate cross-stock price impacts of order flows that are initiated by computer algorithms and human brokers, respectively:

$$RA_t = \alpha + \sum_{i=1}^{6} \beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \beta_{i,w} RA_{t-i} D^w + \sum_{i=0}^{6} \gamma_i MVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \gamma_{i,w} MVA_{t-i} D^w + \sum_{i=1}^{6} \delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \delta_{i,w} RC_{t-i} D^w + \sum_{i=0}^{6} \theta_i MVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \theta_{i,w} MVC_{t-i} D^w + \epsilon_t\ ,$$

$$RA_t = \alpha + \sum_{i=1}^{6} \beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \beta_{i,w} RA_{t-i} D^w + \sum_{i=0}^{6} \gamma_i HVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \gamma_{i,w} HVA_{t-i} D^w + \sum_{i=1}^{6} \delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \delta_{i,w} RC_{t-i} D^w + \sum_{i=0}^{6} \theta_i HVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \theta_{i,w} HVC_{t-i} D^w + \epsilon_t\ .$$

RA_t (RC_t) denotes the quote returns in announcing (rival) firms over the five minute interval t. The quote return is defined as the natural logarithm of quote midpoint change during the five minute interval t. MVA_t (MVC_t) denotes the *computer-initiated* net order flows (trade imbalances) in announcing (rival) firms over the five minute interval t; HVA_t (HVC_t) denotes the *human-initiated* net order flows (trade imbalances) in announcing (rival) firms over the five minute interval t. The net order flow is calculated as buyer-initiated volume minus seller-initiated volume during the five minute interval t. For *both* equations, the dependent variable (RA_t) is the contemporaneous return of the announcing firm, and the independent variables include lagged returns (six lags) in both the announcing firm ($\sum_{i=1}^{6} RA_{t-i}$) and the rival firm ($\sum_{i=1}^{6} RC_{t-i}$). The independent variables in the *first* equation also contain contemporaneous and lagged *computer-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} MVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} MVC_{t-i}$). The independent variables in the *second* equation also contain contemporaneous and lagged *human-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} HVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} HVC_{t-i}$). For each individual stock, all variables are standardized by first subtracting its daily mean and then dividing by its daily standard deviation. This procedure allows for pooling across stocks so as to increase the empirical test power. We estimate cross-stock price impacts of algorithmic and non-algorithmic order flows, respectively, during both benchmark and event periods. We define day 0 as the event day when the earnings announcement is released. The benchmark period spans ten trading days surrounding the event day, which includes both the period between day –15 and day –11 and the period between day +11 and day +15. The event period consist of five days (days –2 to +2) around the earnings announcement. D^w is a dummy variable indicating the pre-event window (days –2 to –1), event day window (day 0), and post-event window (days +1 to +2); D^w is equal to one for the corresponding event window and zero otherwise. The cross-stock price impacts are measured as the sums of the estimated coefficients on rival-firm algorithmic and non-algorithmic order flows, respectively. The null hypothesis is that the sums of cross-stock coefficients estimates are not significantly different from zero (i.e., $\sum_{i=0}^{6} \theta_i = 0$ for all periods and $\sum_{i=0}^{i=6} \theta_{i,w} D^w = 0$ for event windows). The estimated values of coefficients restrictions (i.e., sums of cross-stock coefficients estimates) are presented; the corresponding *p*-values are reported in parentheses below the estimates.

Panel A: High absolute cumulative abnormal return

Dependent Variable: Announcing-Firm Return (RA_t)				
Explanatory Variables	All Periods	Pre-Event Interaction	Event Day Interaction	Post-Event Interaction
Order Flows Initiated by Computer Algorithms				
Rival-Firm Returns	0.0247**	-0.0092	-0.0164	-0.0455
	(0.0290)	(0.7412)	(0.6569)	(0.1196)
Rival-Firm Order Flows	0.0241**	-0.0224	0.0191	-0.0291
	(0.0212)	(0.3781)	(0.5970)	(0.2768)
Order Flows Initiated by Human Brokers				
Rival-Firm Returns	0.0395***	-0.0248	0.0177	-0.0388
	(0.0005)	(0.3768)	(0.6371)	(0.1897)
Rival-Firm Order Flows	0.0240	-0.0685*	-0.0738	-0.0124
	(0.1388)	(0.0649)	(0.1599)	(0.7599)

Panel B: Low absolute cumulative abnormal return

Dependent Variable: Announcing-Firm Return (RA_t)				
Explanatory Variables	All Periods	Pre-Event Interaction	Event Day Interaction	Post-Event Interaction
Order Flows Initiated by Computer Algorithms				
Rival-Firm Returns	0.0297**	-0.0106	0.0200	-0.0180
	(0.0114)	(0.7164)	(0.5966)	(0.4978)
Rival-Firm Order Flows	0.0095	0.0067	0.0951***	-0.0307
	(0.3778)	(0.7963)	(0.0048)	(0.2202)
Order Flows Initiated by Human Brokers				
Rival-Firm Returns	0.0258**	-0.0191	0.0318	-0.0165
	(0.0293)	(0.5212)	(0.4070)	(0.5460)
Rival-Firm Order Flows	0.0099	0.0224	-0.0333	-0.0086
	(0.5340)	(0.5572)	(0.4878)	(0.8178)

Table VIII. Announcement releasing time and cross-stock price impacts of information-based trading in rivals

This table presents the estimated cross-stock price impacts of order flows by considering whether the earnings announcement is released during or after trading hours. Panel A of Table VIII presents results for the announcement is released during trading hours; Panel B of Table VIII presents results for the announcement is released after trading hours. Specifically, for both Panel A and B, we run the following two regression models of Equations (5) and (6) to estimate cross-stock price impacts of order flows that are initiated by computer algorithms and human brokers, respectively:

$$RA_t = \alpha + \sum_{i=1}^{6} \beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \beta_{i,w} RA_{t-i} D^w + \sum_{i=0}^{6} \gamma_i MVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \gamma_{i,w} MVA_{t-i} D^w + \sum_{i=1}^{6} \delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \delta_{i,w} RC_{t-i} D^w + \sum_{i=0}^{6} \theta_i MVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \theta_{i,w} MVC_{t-i} D^w + \epsilon_t \ ,$$

$$RA_t = \alpha + \sum_{i=1}^{6} \beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \beta_{i,w} RA_{t-i} D^w + \sum_{i=0}^{6} \gamma_i HVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \gamma_{i,w} HVA_{t-i} D^w + \sum_{i=1}^{6} \delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \delta_{i,w} RC_{t-i} D^w + \sum_{i=0}^{6} \theta_i HVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \theta_{i,w} HVC_{t-i} D^w + \epsilon_t \ .$$

RA_t (RC_t) denotes the quote returns in announcing (rival) firms over the five minute interval t. The quote return is defined as the natural logarithm of quote midpoint change during the five minute interval t. MVA_t (MVC_t) denotes the *computer-initiated* net order flows (trade imbalances) in announcing (rival) firms over the five minute interval t; HVA_t (HVC_t) denotes the *human-initiated* net order flows (trade imbalances) in announcing (rival) firms over the five minute interval t. The net order flow is calculated as buyer-initiated volume minus seller-initiated volume during the five minute interval t. For *both* equations, the dependent variable (RA_t) is the contemporaneous return of the announcing firm, and the independent variables include lagged returns (six lags) in both the announcing firm ($\sum_{i=1}^{6} RA_{t-i}$) and the rival firm ($\sum_{i=1}^{6} RC_{t-i}$). The independent variables in the *first* equation also contain contemporaneous and lagged *computer-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} MVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} MVC_{t-i}$). The independent variables in the *second* equation also contain contemporaneous and lagged *human-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} HVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} HVC_{t-i}$). For each individual stock, all variables are standardized by first subtracting its daily mean and then dividing by its daily standard deviation. This procedure allows for pooling across stocks so as to increase the empirical test power. We estimate cross-stock price impacts of algorithmic and non-algorithmic order flows, respectively, during both benchmark and event periods. We define day 0 as the event day when the earnings announcement is released. The benchmark period spans ten trading days surrounding the event day, which includes both the period between day –15 and day –11 and the period between day +11 and day +15. The event period consist of five days (days –2 to +2) around the earnings announcement. D^w is a dummy variable indicating the pre-event window (days –2 to –1), event day window (day 0), and post-event window (days +1 to +2); D^w is equal to one for the corresponding event window and zero otherwise. The cross-stock price impacts are measured as the sums of the estimated coefficients on rival-firm algorithmic and non-algorithmic order flows, respectively. The null hypothesis is that the sums of cross-stock coefficients estimates are not significantly different from zero (i.e., $\sum_{i=0}^{6} \theta_i = 0$ for all periods and $\sum_{i=0}^{i=6} \theta_{i,w} D^w = 0$ for event windows). The estimated values of coefficients restrictions (i.e., sums of cross-stock coefficients estimates) are presented; the corresponding *p*-values are reported in parentheses below the estimates.

Panel A: Announcement released during trading hours

Dependent Variable: Announcing-Firm Return (RA_t)				
Explanatory Variables	All Periods	Pre-Event Interaction	Event Day Interaction	Post-Event Interaction
Order Flows Initiated by Computer Algorithms				
Rival-Firm Returns	0.0231***	-0.0019	0.0092	-0.0321
	(0.0068)	(0.9306)	(0.7450)	(0.1177)
Rival-Firm Order Flows	0.0168**	0.0151	0.0645**	-0.0228
	(0.0319)	(0.4379)	(0.0139)	(0.2341)
Order Flows Initiated by Human Brokers				
Rival-Firm Returns	0.0254***	-0.0090	0.0228	-0.0250
	(0.0032)	(0.6798)	(0.4279)	(0.2351)
Rival-Firm Order Flows	0.0145	0.0016	-0.0389	-0.0149
	(0.2212)	(0.9545)	(0.2973)	(0.6033)

Panel B: Announcement released after trading hours

Dependent Variable: Announcing-Firm Return (RA_t)				
Explanatory Variables	All Periods	Pre-Event Interaction	Event Day Interaction	Post-Event Interaction
Order Flows Initiated by Computer Algorithms				
Rival-Firm Returns	0.0650**	-0.0780	-0.0619	-0.0015
	(0.0145)	(0.1590)	(0.3960)	(0.9813)
Rival-Firm Order Flows	0.0189	-0.1475***	0.0218	-0.0821
	(0.4578)	(0.0050)	(0.7581)	(0.1557)
Order Flows Initiated by Human Brokers				
Rival-Firm Returns	0.0958***	-0.0773	-0.0187	-0.0461
	(0.0003)	(0.1803)	(0.8067)	(0.4876)
Rival-Firm Order Flows	0.0285	-0.1630**	-0.1086	0.0574
	(0.4437)	(0.0296)	(0.3292)	(0.5415)

Table IX. Decomposing order flows by computer-human maker-taker

This table presents the estimated cross-stock price impacts by breaking down net order flows (i.e., buyer-initiated transaction minus seller-initiated transaction) into four possible categories: computer (take liquidity) and computer (make liquidity), computer (take liquidity) and human (make liquidity), human (take liquidity) and computer (make liquidity), human (take liquidity) and human (make liquidity). Specifically, for each order flow category, we run the following two regression models of Equations (5) and (6) to estimate cross-stock price impacts of order flows that are initiated by computer algorithms and human brokers, respectively:

$$RA_t = \alpha + \sum_{i=1}^{6} \beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \beta_{i,w} RA_{t-i} D^w + \sum_{i=0}^{6} \gamma_i MVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \gamma_{i,w} MVA_{t-i} D^w + \sum_{i=1}^{6} \delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \delta_{i,w} RC_{t-i} D^w + \sum_{i=0}^{6} \theta_i MVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \theta_{i,w} MVC_{t-i} D^w + \epsilon_t \ ,$$

$$RA_t = \alpha + \sum_{i=1}^{6} \beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \beta_{i,w} RA_{t-i} D^w + \sum_{i=0}^{6} \gamma_i HVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \gamma_{i,w} HVA_{t-i} D^w + \sum_{i=1}^{6} \delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \delta_{i,w} RC_{t-i} D^w + \sum_{i=0}^{6} \theta_i HVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \theta_{i,w} HVC_{t-i} D^w + \epsilon_t \ .$$

RA_t (RC_t) denotes the quote returns in announcing (rival) firms over the five minute interval t. The quote return is defined as the natural logarithm of quote midpoint change during the five minute interval t. MVA_t (MVC_t) denotes the *computer-initiated* net order flows (trade imbalances) in announcing (rival) firms over the five minute interval t; HVA_t (HVC_t) denotes the *human-initiated* net order flows (trade imbalances) in announcing (rival) firms over the five minute interval t. The net order flow is calculated as buyer-initiated volume minus seller-initiated volume during the five minute interval t. For *both* equations, the dependent variable (RA_t) is the contemporaneous return of the announcing firm, and the independent variables include lagged returns (six lags) in both the announcing firm ($\sum_{i=1}^{6} RA_{t-i}$) and the rival firm ($\sum_{i=1}^{6} RC_{t-i}$). The independent variables in the *first* equation also contain contemporaneous and lagged *computer-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} MVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} MVC_{t-i}$). The independent variables in the *second* equation also contain contemporaneous and lagged *human-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} HVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} HVC_{t-i}$). For each individual stock, all variables are standardized by first subtracting its daily mean and then dividing by its daily standard deviation. This procedure allows for pooling across stocks so as to increase the empirical test power, and enables us to assume that the error terms are homoscedastic. We estimate cross-stock price impacts of algorithmic and non-algorithmic order flows, respectively, during both benchmark and event periods. We define day 0 as the event day when the earnings announcement is released. The benchmark period spans ten trading days surrounding the event day, which includes both the period between day –15 and day –11 and the period between day +11 and day +15. The event period consist of five days (days –2 to +2) around the earnings announcement. D^w is a dummy variable indicating the pre-event window (days –2 to –1), event day window (day 0), and post-event window (days +1 to +2); D^w is equal to one for the corresponding event window and zero otherwise. The cross-stock price impacts are measured as the sums of the estimated coefficients on rival-firm algorithmic and non-algorithmic order flows, respectively. The null hypothesis is that the sums of cross-stock coefficients estimates are not significantly different from zero (i.e., $\sum_{i=0}^{6} \theta_i = 0$ for all periods and $\sum_{i=0}^{i=6} \theta_{i,w} D^w = 0$ for event windows). The estimated values of coefficients restrictions (i.e., sums of cross-stock coefficients estimates) are presented; the corresponding *p*-values are reported in parentheses below the estimates.

Dependent Variable: Announcing-Firm Return (RA_t)				
Explanatory Variables	All Periods	Pre-Event Interaction	Event Day Interaction	Post-Event Interaction
Computer Take & Computer Make				
Rival-Firm Returns	0.0325***	-0.0184	0.0009	-0.0324
	(0.0001)	(0.3665)	(0.9719)	(0.1041)
Rival-Firm Order Flows	0.0221***	-0.0199	0.0227	0.0140
	(0.0083)	(0.3340)	(0.4272)	(0.4984)
Computer Take & Human Make				
Rival-Firm Returns	0.0345***	-0.0106	0.0073	-0.0257
	(0.0000)	(0.6046)	(0.7857)	(0.1996)
Rival-Firm Order Flows	0.0114	-0.0375	0.0825***	-0.0630**
	(0.2608)	(0.1273)	(0.0096)	(0.0104)
Human Take & Computer Make				
Rival-Firm Returns	0.0343***	-0.0211	0.0114	-0.0287
	(0.0000)	(0.3002)	(0.6711)	(0.1501)
Rival-Firm Order Flows	0.0172	0.0031	-0.0864**	-0.0013
	(0.1449)	(0.9118)	(0.0200)	(0.9616)
Human Take & Human Make				
Rival-Firm Returns	0.0331***	-0.0099	0.0106	-0.0299
	(0.0001)	(0.6308)	(0.6933)	(0.1370)
Rival-Firm Order Flows	0.0051	-0.0904**	0.0279	0.0130
	(0.7740)	(0.0346)	(0.6237)	(0.7637)

Table X. Controlling for market wide effect

This table presents the estimated cross-stock price impacts of algorithmic and non-algorithmic order flows, respectively, by controlling for market wide effect. We run the following two regression models that originate from Equations (5) and (6) to estimate cross-stock price impacts of order flows that are initiated by computer algorithms and human brokers, respectively:

$$RA_t = \alpha + \lambda RM_t + \sum_{i=1}^{6} \beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \beta_{i,w} RA_{t-i} D^w + \sum_{i=0}^{6} \gamma_i MVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \gamma_{i,w} MVA_{t-i} D^w + \sum_{i=1}^{6} \delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \delta_{i,w} RC_{t-i} D^w + \sum_{i=0}^{6} \theta_i MVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \theta_{i,w} MVC_{t-i} D^w + \epsilon_t \ ,$$

$$RA_t = \alpha + \lambda RM_t + \sum_{i=1}^{6} \beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \beta_{i,w} RA_{t-i} D^w + \sum_{i=0}^{6} \gamma_i HVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \gamma_{i,w} HVA_{t-i} D^w + \sum_{i=1}^{6} \delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \delta_{i,w} RC_{t-i} D^w + \sum_{i=0}^{6} \theta_i HVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \theta_{i,w} HVC_{t-i} D^w + \epsilon_t \ .$$

RM_t denotes the quote returns in All Ordinary Index over the five minute interval t. RA_t (RC_t) denotes the quote returns in announcing (rival) firms over the five minute interval t. The quote return is defined as the natural logarithm of quote midpoint change during the five minute interval t. MVA_t (MVC_t) denotes the *computer-initiated* net order flows (trade imbalances) in announcing (rival) firms over the five minute interval t; HVA_t (HVC_t) denotes the *human-initiated* net order flows (trade imbalances) in announcing (rival) firms over the five minute interval t. The net order flow is calculated as buyer-initiated volume minus seller-initiated volume during the five minute interval t. For *both* equations, the dependent variable (RA_t) is the contemporaneous return of the announcing firm, and the independent variables include lagged returns (six lags) in both the announcing firm ($\sum_{i=1}^{6} RA_{t-i}$) and the rival firm ($\sum_{i=1}^{6} RC_{t-i}$). The independent variables in the *first* equation also contain contemporaneous and lagged *computer-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} MVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} MVC_{t-i}$). The independent variables in the *second* equation also contain contemporaneous and lagged *human-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} HVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} HVC_{t-i}$). For each individual stock, all variables are standardized by first subtracting its daily mean and then dividing by its daily standard deviation. This procedure allows for pooling across stocks so as to increase the empirical test power. We estimate cross-stock price impacts of algorithmic and non-algorithmic order flows, respectively, during both benchmark and event periods. We define day 0 as the event day when the earnings announcement is released. The benchmark period spans ten trading days surrounding the event day, which includes both the period between day –15 and day –11 and the period between day +11 and day +15. The event period consist of five days (days –2 to +2) around the earnings announcement. D^w is a dummy variable indicating the pre-event window (days –2 to –1), event day window (day 0), and post-event window (days +1 to +2); D^w is equal to one for the corresponding event window and zero otherwise. The cross-stock price impacts are measured as the sums of the estimated coefficients on rival-firm algorithmic and non-algorithmic order flows, respectively. The null hypothesis is that the sums of cross-stock coefficients estimates are not significantly different from zero (i.e., $\sum_{i=0}^{6} \theta_i = 0$ for all periods and $\sum_{i=0}^{i=6} \theta_{i,w} D^w = 0$ for event windows). The estimated values of coefficients restrictions (i.e., sums of cross-stock coefficients estimates) are presented; the corresponding *p*-values are reported in parentheses below the estimates.

Dependent Variable: Announcing-Firm Return (RA_t)				
Explanatory Variables	All Periods	Pre-Event Interaction	Event Day Interaction	Post-Event Interaction
Order Flows Initiated by Computer Algorithms				
Rival-Firm Returns	0.0277***	-0.0096	0.0005	-0.0290
	(0.0007)	(0.6326)	(0.9860)	(0.1395)
Rival-Firm Order Flows	0.0176**	-0.0078	0.0558**	-0.0282
	(0.0195)	(0.6708)	(0.0230)	(0.1221)
Order Flows Initiated by Human Brokers				
Rival-Firm Returns	0.0333***	-0.0197	0.0156	-0.0281
	(0.0001)	(0.3345)	(0.5621)	(0.1615)
Rival-Firm Order Flows	0.0165	-0.0224	-0.0485	-0.0072
	(0.1462)	(0.4000)	(0.1705)	(0.7937)

Table XI. Alternative length of time interval for calculating net order flows

This table presents the estimated cross-stock price impacts of algorithmic and non-algorithmic order flows, respectively, with alternative length of time interval for calculating net order flows (ten minutes). We run the following two regression models of Equations (5) and (6) to estimate cross-stock price impacts of order flows that are initiated by computer algorithms and human brokers, respectively:

$$RA_t = \alpha + \sum_{i=1}^{6} \beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \beta_{i,w} RA_{t-i} D^w + \sum_{i=0}^{6} \gamma_i MVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \gamma_{i,w} MVA_{t-i} D^w + \sum_{i=1}^{6} \delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \delta_{i,w} RC_{t-i} D^w + \sum_{i=0}^{6} \theta_i MVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \theta_{i,w} MVC_{t-i} D^w + \epsilon_t\ ,$$

$$RA_t = \alpha + \sum_{i=1}^{6} \beta_i RA_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \beta_{i,w} RA_{t-i} D^w + \sum_{i=0}^{6} \gamma_i HVA_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \gamma_{i,w} HVA_{t-i} D^w + \sum_{i=1}^{6} \delta_i RC_{t-i} + \sum_{i=1;w=1}^{i=6;w=3} \delta_{i,w} RC_{t-i} D^w + \sum_{i=0}^{6} \theta_i HVC_{t-i} + \sum_{i=0;w=1}^{i=6;w=3} \theta_{i,w} HVC_{t-i} D^w + \epsilon_t\ .$$

RA_t (RC_t) denotes the quote returns in announcing (rival) firms over the ten minute interval t. The quote return is defined as the natural logarithm of quote midpoint change during the ten minute interval t. MVA_t (MVC_t) denotes the *computer-initiated* net order flows (trade imbalances) in announcing (rival) firms over the ten minute interval t; HVA_t (HVC_t) denotes the *human-initiated* net order flows (trade imbalances) in announcing (rival) firms over the ten minute interval t. The net order flow is calculated as buyer-initiated volume minus seller-initiated volume during the ten minute interval t. For *both* equations, the dependent variable (RA_t) is the contemporaneous return of the announcing firm, and the independent variables include lagged returns (six lags) in both the announcing firm ($\sum_{i=1}^{6} RA_{t-i}$) and the rival firm ($\sum_{i=1}^{6} RC_{t-i}$). The independent variables in the *first* equation also contain contemporaneous and lagged *computer-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} MVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} MVC_{t-i}$). The independent variables in the *second* equation also contain contemporaneous and lagged *human-initiated* net order flows (six lags) in both the announcing firm ($\sum_{i=0}^{6} HVA_{t-i}$) and the rival firm ($\sum_{i=0}^{6} HVC_{t-i}$). For each individual stock, all variables are standardized by first subtracting its daily mean and then dividing by its daily standard deviation. This procedure allows for pooling across stocks so as to increase the empirical test power, and enables us to assume that the error terms are homoscedastic. We estimate cross-stock price impacts of algorithmic and non-algorithmic order flows, respectively, during both benchmark and event periods. We define day 0 as the event day when the earnings announcement is released. The benchmark period spans ten trading days surrounding the event day, which includes both the period between day –15 and day –11 and the period between day +11 and day +15. The event period consist of five days (days –2 to +2) around the earnings announcement. D^w is a dummy variable indicating the pre-event window (days –2 to –1), event day window (day 0), and post-event window (days +1 to +2); D^w is equal to one for the corresponding event window and zero otherwise. The cross-stock price impacts are measured as the sums of the estimated coefficients on rival-firm algorithmic and non-algorithmic order flows, respectively. The null hypothesis is that the sums of cross-stock coefficients estimates are not significantly different from zero (i.e., $\sum_{i=0}^{6} \theta_i = 0$ for all periods and $\sum_{i=0}^{i=6} \theta_{i,w} D^w = 0$ for event windows). The estimated values of coefficients restrictions (i.e., sums of cross-stock coefficients estimates) are presented; the corresponding *p*-values are reported in parentheses below the estimates.

Dependent Variable: Announcing-Firm Return (RA_t)				
Explanatory Variables	All Periods	Pre-Event Interaction	Event Day Interaction	Post-Event Interaction
Order Flows Initiated by Computer Algorithms				
Rival-Firm Returns	0.0307***	-0.0062	-0.0220	-0.0092
	(0.0078)	(0.8250)	(0.5464)	(0.7396)
Rival-Firm Order Flows	0.0212**	0.0018	0.0758**	0.0152
	(0.0445)	(0.9447)	(0.0254)	(0.5547)
Order Flows Initiated by Human Brokers				
Rival-Firm Returns	0.0388***	-0.0049	0.0062	0.0013
	(0.0008)	(0.8606)	(0.8690)	(0.9639)
Rival-Firm Order Flows	0.0065	-0.0068	-0.0657	0.0087
	(0.6508)	(0.8380)	(0.1470)	(0.8040)