Insider Trading Filing and Intra-Industry Information Transfer[1]

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This paper examines whether insider trading disclosures have information transfer effects within the same industry. We find that on the dates an insider trade is filed with the SEC, the stock returns of industry peers are positively correlated with the direction of the trade, i.e., industry peers have positive (negative) returns when purchases (sales) are disclosed. This effect varies across firms: insider trading filings from industry leaders have stronger information transfer effects on their industry peers while rival firms experience less positive information transfer effects. Our results are driven by insider sales, prompting us to investigate the relation between insider selling and industry-level information. We find that insider selling occurs when industries are overvalued. Taken together, our evidence suggests that insider trading filings contain industry-level information and affect the stock returns of industry peers.

JEL Classification: G34, J33, K31, M52
Keywords: insider trading filing, information transfer, industry leaders, rival firms, insider purchases, insider sales

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ABSTRACT

This paper examines whether insider trading disclosures have information transfer effects within the same industry. We find that on the dates an insider trade is filed with the SEC, the stock returns of industry peers are positively correlated with the direction of the trade, i.e., industry peers have positive (negative) returns when purchases (sales) are disclosed. This effect varies across firms: insider trading filings from industry leaders have stronger information transfer effects on their industry peers while rival firms experience less positive information transfer effects. Our results are driven by insider sales, prompting us to investigate the relation between insider selling and industry-level information. We find that insider selling occurs when industries are overvalued. Taken together, our evidence suggests that insider trading filings contain industry-level information and affect the stock returns of industry peers.

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1. Introduction

This study provides evidence of information transfers to industry peers from a firm's insider trading disclosures. Previous literature on information transfer finds that a firm's public disclosures have information transfer effects in settings such as earnings announcements and management forecasts (e.g., Foster [1981], Baginski [1987], Han and Wild [1990], and Kim et al. [2008]). Prior literature on insider trading finds that insider trading filings have a significant impact on the stock returns of filing firms (e.g., Brochet [2010] and Veenman [2012]). However, to the best of our knowledge, no study has examined whether the disclosure of insider trades impacts non-disclosing firms in the same industry. This paper aims to fill this void.

Insiders are contrarian investors who appear to trade on market misvaluation (e.g., Ali et al. [2011], Piotroski and Roulstone [2005]). As insiders have more accurate judgments about their own firms' value compared to outside investors, they can trade against the market when share price deviates from the insiders' estimate of intrinsic value. This misvaluation can be at the industry level. For example, in 2000, at the end of the internet bubble period, insiders and institutions were net sellers (e.g., Berman [2002] and Griffin et al. [2011]). Because firms in the same industry operate in a similar business environment, face similar suppliers and customers, and experience common industry shocks, insiders have knowledge of industry-wide information through the private observation of their own firms. This information may not be available to, or properly processed by, public investors. Given the information advantage of insiders with regard to industry-level information, it is possible that the disclosure of insider trades will send a signal about industry misvaluation to investors in industry peers. A real-world example illustrates this reasoning. On 22nd May 2012, Facebook disclosed that CEO Mark Zuckerberg sold 30.2 million Facebook shares (equivalent to 1.41% of shares outstanding). On that date, Facebook experienced a decrease in price as did other firms related to the social network service. For example, the price of Linkedin decreased by 2.02% and the price of Renren (the so-called "Chinese Facebook"), decreased by 0.84%.

We use insider trading intensity, measured as the number of shares traded by insiders divided by the number of shares outstanding (with a positive sign for insider purchases and a negative sign for insider sales), to proxy for the signal in SEC filings disclosing the existence of a trade. The intuition is that insider purchases (sales) can signal that the insider's industry is relatively undervalued (overvalued) and the amount of trading can convey the strength of the signal. We test this intuition by regressing the abnormal returns of non-filing firms in the same four-digit SIC industry[1] on the signed insider trading intensity controlling for firm size, book-to-market ratio, and short term momentum. We find that the signed insider trading intensity is significantly and positively correlated with industry peers' abnormal returns, suggesting the existence of positive information transfer effects from the disclosure of insider trading.

We next examine whether the insider trading filings of industry leaders have a stronger impact on their industry peers. Lo and MacKinlay [1990] and Hou [2007] find that large firms lead small firms in stock returns. Therefore, it is possible that the signal from the insider trading filings of bigger firms have a stronger impact than that of smaller firms. Following Hou [2007], we assume large firms play leading roles in an industry. We use two proxies to measure firm size, (sales revenue and total assets), and define firms in the top decile of firm size as industry leaders. We interact an indicator variable for being an industry leader with the signed insider trading intensity and find the interaction is significantly positive, suggesting that insider trading filings of industry leaders have a stronger impact on their industry peers than those from other firms in the same industry.

[1] We use the term "non-filing firms in the same industry" or "industry peers" interchangeably in the paper.

In addition, we examine whether the information transfer effects of insider trading filings are different for rival peer firms than for non-rival peer firms. Kim et al. [2008] find that rival firms' prices react to management forecast announcements in the opposite direction of the announcement news. This is possibly due to the announcement signaling shifts in competition which negate the positive information transfer arising from industry commonalities. Following this argument, it is possible that the information transfer effects of insider trading filings will be less positive for rival firms than for non-rival firms. To test this possibility, we obtain two measures of whether firms are industry rivals. The first is based on the market reaction to other firms' earnings announcements (Kim et al. [2008]) and the second is based on industry-adjusted return on equity correlation (Lang and Stulz [1992]). We include indicator variables for rival status and their interactions with the signed insider trading intensity in our regressions. We find that rival firms experience less positive information transfer than non-rival firms, consistent with prior findings in settings such as bankruptcy announcements, dividend revisions, and management forecasts (e.g., Lang and Stulz [1992], Laux et al. [1998], and Kim et al. [2008]).

We separate our sample by insider purchase filings vs. insider sales filings to examine whether the information transfer effects differ across positive and negative signals. We find that the information transfer effects are stronger for insider sales filings than for insider purchases filings, consistent with the findings of Han et al. [1989] that bad-news forecasts have more positive information transfer effects than good-news forecasts. In further tests we find that insider sales are more capable than purchases in predicting the market reaction to future earnings announcements of industry peers, that insider sales have a stronger association with industry misvaluation than insider purchases, and that insider sales contain more industry-level information than insider purchases. These asymmetries are consistent with disclosures of insider sales having a greater information transfer effect than disclosures of insider purchases. We theorize that insider sales are more industry-related than insider purchases for three reasons. First, in bad times, firms' returns tend to be more correlated than in good times (Ang and Chen [2002]). Second, the greater litigation risk from selling on bad news (relative to buying on good news) suggests that insiders are less likely to sell on firm-specific news than they are to buy on firm-specific news (Cheng and Lo [2006]). Since industry-level information is not private and trading upon that is less likely to be prosecuted, we expect insiders would take advantage of their knowledge about industry-level information and trade against the industry misvaluation. Third, insiders can exploit industry-level bad news by selling more easily than they can exploit industry-level good news by buying. Insiders' substantial equity positions enable them to take advantage of industry overvaluation (by selling their shares); in contrast, trading on industry undervaluation requires sufficient cash holdings. In addition, insiders' wealth is strongly correlated with their firm's prospects so purchases result in increased idiosyncratic risk as opposed to sales which diversify the insider's portfolio. All else equal, we expect insiders should be more sensitive to negative industry-level news than positive industry-level news which is consistent with our empirical findings.

Our paper contributes to the prior literature in two main areas. First, it contributes to the insider trading literature by documenting that the disclosure of insider trades affects the share prices of non-disclosing firms in the same industry. Previous studies on insider trading tend to emphasize the role of firm-specific information in insider trading (e.g., Piotroski and Roulstone [2004]). We find that insiders trade upon industry-level information as well and the disclosure of insider trades conveys relevant information regarding industry peers. Second, this paper contributes to the information transfer literature. Prior literature in this field documents that public disclosures such as earnings announcements and management forecasts have information transfer effects (Foster [1981], Baginski [1987], Han and Wild [1990], and Kim et al. [2008]). We contribute to this line of literature by showing that insider trading filings also have information transfer effects. Our results have implications for investors who want to understand the role of insider trading filings in conveying information to the market.

The remainder of the paper is organized as follows. Section 2 discusses our sample selection process and research design. Section 3 presents the empirical results. Section 4 discusses the results of additional analyses. Section 5 concludes.

2. Sample Selection and Research Design

2.1 SAMPLE SELECTION

Our initial sample includes insider filings of firms listed on the NYSE, AMEX, or NASDAQ covered in the Thomson Financial Insiders Data Feed over the years 1986 to 2010.[2] The Thomson Financial Insiders Data Feed contains trade information of insiders subject to disclosure requirements as defined in Section 16 of the Securities Exchange Act of 1934. We focus on filings of valid share purchases and sales only and include all insiders in the final sample.[3,4] Following previous studies, we further limit the sample by requiring that share codes in CRSP be 10 or 11 and we exclude the following observations: (1) filings published three days before or after an earnings announcement or a management forecast announcement; 2) filings where the trade size is less than 100 shares or the trade price is less than $2; (3) filings with

[2] Prior to the Sarbanes-Oxley act, insiders had until the tenth day of the following month to report a trade. Sarbanes-Oxley required insiders to disclose their trades within two business days. When splitting the sample pre and post-Sarbanes-Oxley, we find similar results.
[3] A valid transaction is one without a cleanse code of "A" or "S."
[4] The inferences of our results are similar when insiders are restricted to top five officers (Chairman of the Board, Chief Executive Officer, Chief Operating Officer, Chief Financial Officer, and President).

traded prices outside the range between the daily low and high prices reported in CRSP; (4) filings where the trade size exceeds total shares outstanding in CRSP; and (5) filings where the number of shares traded exceeds total daily trading volume in CRSP. To be included in our sample, we also require that stock return and financial data are available in CRSP and Compustat, respectively. We obtain analyst forecast data from I/B/E/S.

To form the sample for our main analyses, we first obtain insider trading filing dates (subject to the above restrictions) and then match the filing firm-dates with the CRSP and Compustat non-filing firms based on four-digit SIC code.[5] Our final sample has 359,367 filing-dates and 24,799,150 industry-peers-filing-date observations.

2.2 MEASUREMENT OF INSIDER TRADING FILING NEWS

To examine the information transfer effects of an insider trading filing, we need to measure the news in the filing. One candidate measure is the firm-specific market reaction to the disclosure of the insider trade. Its advantage is that it captures the market's assessment of the valuation implications of the insider-trading disclosure. However, it also captures other industry news besides the piece reflected in the trade and hence can result in a reverse causality problem. A similar issue arises in the information transfer studies regarding earnings announcement and management guidance (Han et al. [1989], Han and Wild [1990] and Kim et al. [2008]). Those studies prefer unexpected earnings or unexpected managers' forecasts over the cumulative abnormal return around the announcements as proxies for the announcement news since the former type of measures are independent of industry peers and other industry-level news. For this reason, we construct a non-market measure of insider trading filing news, the signed insider

[5] We require that an industry has more than 2 firms in the matching process. The results are quantitatively similar when we include observations from industries with only two firms.

trading intensity (*TradeInt*), defined as: the number of shares reported on insiders' Form 4 filings on a given firm-day, scaled by shares outstanding, with a positive sign for purchases and a negative sign for sales.[6] Prior papers on insider trading generally find that the disclosure of insider purchases is accompanied by significantly positive abnormal returns for the filing firm and the disclosure of insider sales is followed by significantly negative abnormal returns for the filing firm, with these effects increasing in trade size (e.g., Brochet [2010] and Veenman [2012]).[7] Therefore, our signed insider trading intensity measure should capture differences between purchases and sales and will give greater weight to trades with larger size.

2.3 REGRESSION MODEL FOR THE MAIN RESULTS

To examine whether the information in insider trades transfers to industry peers, we regress the cumulative abnormal return of industry peers on the signed insider trading intensity. Brochet [2010] finds that the effect of insider trade filings on the stock price of the filing firm is concentrated in the three-day period starting on the filing date. Hence, we choose the three-day period starting on the filing date to calculate the cumulative abnormal return of non-filing firms. In addition, we follow Lakonishok and Lee [2001] and include *Size* and *BM* to control for size and book-to-market effects and include the non-filing firms' recent returns (*CAR_17*) to control for momentum effects.

The regression model is as below:

[6] As a robustness check, we measure the disclosure news as the disclosing firm's 3-day cumulative abnormal return beginning on the date of the insider trading filing. The results are quantitatively similar. We do not include these results in the main results because, as discussed, this measure could be confounded with other industry news and is susceptible to a reverse causality explanation.

[7] To further verify the informativeness of insider trading intensity, we regress the disclosing firm's 3-day cumulative abnormal return beginning on the date of the insider trading filing (CAR02) on insider trading intensity with control of firm size, book-to-market ratio and short momentum. We find insider trading intensity is significantly associated with the CAR02 and the association is much larger for insider purchase intensity than for insider sales intensity, in line with Brochet [2010] and Veenman [2012].

$$CAR02_{i,t}=\alpha+\beta_1 TradeInt_{i,t}+\beta_2 log(Size)_{i,t}+\beta_3 log(BM)_{i,t}+\beta_4 CAR\_17_{i,t}+\varepsilon_{i,t} \quad (1)$$

where:

CAR02 = the three-day cumulative abnormal return, starting on a Form 4 filing date, for non-filing firms matched based on four-digit SIC code, adjusted for the Fama-French size and book-to-market 5*5 portfolios;

TradeInt = the number of shares as reported on the filed Form 4, scaled by shares outstanding with a positive sign for purchases and a negative sign for sales;

Size = the market capitalization at the beginning of a year;

BM = the ratio of book value of equity on market capitalization at the beginning of a year;

CAR_17 = the seven-day cumulative abnormal returns prior to the Form 4 filing date for non-filing firms matched based on four-digit SIC code adjusted for the Fama-French size and book-to-market 5*5 portfolios, defined as $\sum_{t=-7}^{-1}(r_{i,t} - r_{p,t})$ where $r_{i,t}$ is the return of firm i in day t and $r_{p,t}$ is the return of corresponding Fama-French 5*5 size and book-to-market portfolio in day t.

2.4 REGRESSION MODEL FOR TESTING THE INCREMENTAL EFFECTS OF INDUSTRY LEADERS' FILING

We follow Hou [2007] and rely on size-related variables to identify industry leaders. We use two measures, one based on sales revenue and the other based on total assets. We define those firms with sale revenues or total assets in the top decile of the Compustat population in that year as industry leaders.

To examine whether insider trading filings from industry leaders have stronger information transfer effects, we run the following regression model:

$$CAR02_{i,t}=\alpha+\beta_1 TradeInt_{i,t}*LeaderDum_{i,t}+\beta_2 TradeInt_{i,t}+\beta_3 LeaderDum_{i,t}+\beta_4 log(Size)_{i,t}$$

$$+\beta_5 log(BM)_{i,t}+\beta_6 CAR\_17_{i,t}+\varepsilon_{i,t} \quad (2)$$

where:

LeaderDum = a dummy variable with the value of one for industry leaders and zero for non-leader firms, measured by *LeaderDum1* or *LeaderDum2*, where

LeaderDum1 = a leader dummy with the value of one for firms with sale revenues in the top decile of the Compustat population in that industry year and zero otherwise, and

LeaderDum2= a leader dummy with the value of one for firms with total assets in the top decile of the Compustat population in that industry year and zero otherwise.

All other variables are as defined above.

2.5 REGRESSION MODEL FOR TESTING THE DIFFERENTIAL EFFECTS OF RIVAL FIRMS VS. NON-RIVAL FIRMS

For the purpose of testing the differential effects of information transfer on rival firms vs. non-rival firms, we need to identify rival firms. Kim et al. [2008] use ex-ante approach to collect data on rival firms through *Hoover's* and the firm's 10-K report. By contrast, we use two ex-post approaches to identify rival firms, one based on information transfer effects in the earnings announcement setting and the other based on industry-adjusted return on equity (ROE) correlations.

For the first approach, we look at the information transfer effects in the setting of earnings announcement and assume firms with less positive spillover effects as rival firms, following the spirit of Kim et al. [2008]. To be specific, we regress non-announcement firms' cumulative abnormal return on announcement firms' unexpected earnings (*UEA*), defined as the difference between actual earnings per share and analyst-forecasted earnings per share scaled by the share price 21 days before the announcement, using model (1) above with replacement of filing news (*TradeInt*) with unexpected earnings (*UEA*). We run the regressions for each pair of firms in the same industry and obtain the coefficient on *UEA* (β_{UEA}). We require the number of observations for each regression larger than 12 to ensure the reliability of the estimation. After that, we compare the coefficient (β_{UEA}) with all coefficients we can get by industry and year and define those pairs of firms with β_{UEA} less than the first quartile of the population for both sides of competitors as rival firms (*RivalDum1*).[8]

For the second approach, we rely on industry-adjusted ROE correlation to judge the relation between two firms. For firms in the same industry, non-rival firms are more likely to have a positive correlation in their ROEs while rival firms have less positive correlation in their ROEs. Specifically, we first match each filing firm with non-filing industry peers, then calculate the industry-adjusted ROE correlation in the past ten years, and finally assign the pairs with correlations below the first quartile of the population for two sides of competitors as rival firms (*RivalDum2*). Minimum 12 observations are required to ensure the reliability of the estimation.

After obtaining the dummy variables for rival firms, we run the following regression model:

$$CAR02_{i,t}=\alpha+\beta_1 TradeInt_{i,t}*RivalDum_i+\beta_2 TradeInt_{i,t}+\beta_3 RivalDum_i+\beta_4 log(Size)_{i,t}$$
$$+\beta_5 log(BM)_{i,t}+\beta_6 CAR\_17_{i,t}+\varepsilon_{i,t} \quad (3)$$

where:

RivalDum = an indicator variable with the value of one for rival firms and zero for non-rival firms, measured by *RivalDum1* or *RivalDum2*, where

[8] We find quantitatively similar evidence when rival dummies are defined in the setting of management forecast announcements.

RivalDum1 = an indicator variable that takes the value of one if β_{UEA} is less than the first quartile of the population by industry and year for both sides of competitors and zero otherwise, where β_{UEA} is the coefficient on unexpected earnings, defined as the difference between actual EPS and analyst forecast EPS scaled by the share price 21 days before the announcement, in the regression with dependent variable of non-announcing firms' three-day abnormal return starting on an earnings announcement date of announcing firms and control variables including *SIZE*, *BM*, and *CAR_17* for non-announcing firms, and

RivalDum2 = an indicator variable that takes the value of one if the industry-adjusted ROE correlation between non-filing firms and filing firms in the past ten years is below the first quartile of the population for two sides of competitors and zero otherwise.

All other variables are defined above.

2.6 DO INSIDER TRADING FILINGS PREDICT FUTURE EARNINGS ANNOUNCEMENT NEWS FOR INDUSTRY PEERS?

To further understand whether insider trading filings contain industry-level news, we test whether the signed insider trading intensity (*TradeInt*) predicts industry peers' future earnings announcement news. The intuition is that if insiders trade upon industry-level news then insider trading filings should have predictive power for industry peers' future performance such as future earnings announcement news. In line with prior literature (e.g., Keung et al. [2010]), we measure the earnings announcement news by the cumulative abnormal return (*CAR_11EA*), calculated as the three-day cumulative abnormal return (adjusted for the Fama-French size and book-to-market 5*5 portfolios) starting one day before the earnings announcement. Future earnings announcements are the first earnings announcement for industry peers (based on four-digit SIC) following the insider trading filing date. We regress industry peers' earnings announcement news on the signed insider trading intensity (*TradeInt*). If filing news has any predictive power for industry peers' performance then the coefficient on the signed insider trading intensity (*TradeInt*) should be significantly positive. The regression model is as follows.

$$CAR\_11EA_{i,t+j} = +\beta_1 TradeInt_{i,t} + \varepsilon_{i,t} \quad (4)$$

where:

CAR_11EA = the three-day cumulative abnormal return starting on one day before the earnings announcement date adjusted for the Fama-French size and book-to-market 5*5 portfolios.

TradeInt is as defined earlier.

3. Empirical Results

3.1 DESCRIPTIVE ANALYSIS

Our sample is based on 24,799,150 industry-peer-filing-date observations. The top and bottom one percentiles of the data are winsorized for all variables except those with a natural boundary (i.e., indicator variables). Table 1 reports descriptive statistics (note that *TradeInt*, *CAR02*, *CAR_17*, and *CAR_11EA* are multiplied by 100 to reduce zeroes after the decimal point). The mean and median values of *CAR02* are -0.127% and -0.269%, respectively. The mean of *TradeInt* is -0.065%, suggesting the average insider filing is a sale of under 0.10% of shares outstanding. The mean and median values of *Size* are 1.877 billion dollars and 177 million dollars, respectively. The mean value of *BM* is 0.532. The mean and median values of *CAR_17* are -0.082% and -0.496%, respectively. The average of both *LeaderDum1* and *LeaderDum2* are

0.124 and 0.163, respectively. The mean values of both *RivalDum1* and *RivalDum2* are 0.026 and 0.001, respectively. *CAR_11EA* has mean value of -0.132%.

[Insert Table 1 & 2 here]

Table 2 provides the correlation matrix for all variables used in the main analyses. The Spearman correlation between *TradeInt* and *CAR02* is 0.010, significant at 1% level, consistent with our conjecture that insider trading filings have positive information transfer to industry peers. The correlation between *TradeInt* and *CAR_11EA* is 0.007 also significant at the 1% level, suggesting that insider trading filings have predictive power for industry peers' future earnings announcement news.

3.2 INFORMATION TRANSFER FROM INSIDER TRADING FILING

In this section, we test whether the investors of industry peers react to the signal in insider trading filings.

[Insert Table 3 here]

Table 3 presents the results of estimating equation (1) where we regress industry peers' cumulative abnormal return (*CAR02*) on the signed insider trading intensity (*TradeInt*) after controlling for size, the book-to-market ratio, and momentum. Given the large number of observations and the fact that our dependent variable is a stock return, we cluster standard errors by filing date to control for cross-sectional correlation among the observations.

We first measure the insider trading intensity based on individual filings and use the full sample to run the regressions. The results are reported in Panel A. We find that signed insider trading intensity is significantly positively related to industry peers' cumulative abnormal return after controlling for size, the book-to-market ratio, and momentum (see model 1). In other words, industry peers' prices move in the same direction as the signal in the filing. The coefficients on the proxies for size, the book-to-market ratio, and momentum generally show the desired sign and significance. Economically, the coefficient of 0.141 suggests that industry peers will experience a decrease of 0.039% in price when insiders at a firm report selling 0.275% of shares outstanding (equal to one standard deviation of the shares traded). This decrease is about 30% of the mean cumulative abnormal return of the peer firms of -0.127%.

Han et al. [1989] find that good-news management forecasts have negative information transfer effects while bad-news management forecasts have positive information transfer effects on industry peers. To examine whether the asymmetric information transfer effects exist in the insider trading filing setting, we separate our sample based on the nature of filings news defined by the signed insider trading intensity (*TradeInt*). Filings with positive (negative) *TradeInt* are insider purchases (insider sales) filings. We find that insider purchasing intensity is insignificantly correlated with industry peers' cumulative abnormal returns (see model 2) while insider sales intensity (with a negative sign) is significantly positively correlated with industry peers' cumulative abnormal returns (see model 3). The difference in the coefficients on the signed insider trading intensity between insider purchase filings and insider sales filings is significant at the 10% level. In other words, we find that the positive information transfer effects of insider trading filings come from insider sales filings and the difference between insider purchases filings and insider sales filings is significant in terms of their impact on industry peers' stock return.

We suggest three reasons for the asymmetry in the relation between insider trading and industry-level information. First, correlations among firm returns are stronger when markets face negative shocks than when they face positive shocks (Ang and Chen [2002]). Thus, insiders trading on knowledge of bad news are likely to convey information that is relevant for other firms in the industry. Second, insiders face strong litigation risk from selling ahead of bad news (e.g., Cheng and Lo [2006]). For example, sudden drops in stock price or disclosures of poor performance are likely to result in shareholder lawsuits which place insider trading under scrutiny. However, if the bad news is public, insiders unlikely face lawsuit for selling their shares given that their sales cannot be traced to private, firm-specific information. Third, insiders, who generally hold large equity positions, are easily able to benefit from industry overvaluation by selling their shares. In contrast, benefiting from industry undervaluation requires purchasing shares, a costly undertaking. Further, insiders in general over-weight the shares of their firms in their personal wealth portfolio. They can benefit from diversification when they sell their shares, adjusting their personal portfolios optimally when there is industry overvaluation. In contrast, reacting to industry undervaluation by buying more of their own firm's shares will increase the idiosyncratic risk of their personal portfolios. Thus, giving consideration to portfolio diversification discourages insider purchases but encourages insider sales.

Cohen et al. (2012) find that routine trades are less informative than opportunistic trades. This suggests our results might be biased against by the routine trades. To examine this possibility, we follow Cohen et al. (2012) and define insiders who trade in the same month in the past three years as routine traders and exclude the filings by those traders from our sample. As shown in Panel B, we find our results are generally similar. The reason might be that routine trades' impact on industry peers' price is small, matched with the small impact on their own share price, and the information transfer coefficient might not be biased downward.

In our sample, there are some industry dates having more than one insider trading filing, i.e., two or more firms in the same industry file insider trades on the same date. In our tests in Panel A, we keep all filings separate in order to examine the differential effects of filings from different firms within the same industry (e.g., industry leaders vs. industry followers). For robustness, we estimate equation (1) after combining firm-day filings at the industry level. Panel C shows the results of estimating equation (1) with industry-day filings as the independent variable; we find our results remain intact.

3.3 INCREMENTAL INFORMATION TRANSFER EFFECTS FOR FILINGS FROM INDUSTRY LEADERS

Lo and MacKinlay [1990] and Hou [2007] find there is an asymmetric lead-lag effect from big firms to small firms but not vice versa. Based on this finding, we examine whether the insider trading filings of industry leaders have stronger information transfer effects. We construct indicator variables (*LeaderDum*) for industry leaders based on sales revenue and total assets and interact these indicators with the signed insider trading intensity (*TradeInt*). We use the coefficients on the interactions to measure the incremental effects from a filing firm being an industry leader.

[Insert Table 4 here]

Table 4 reports the results. After controlling for size, book-to-market, and momentum, we find that the signed insider trading intensity (*TradeInt*) remains significantly positively correlated with industry peers' cumulative abnormal return (*CAR02*) for non-leader firms. Furthermore, we find the coefficients on the interaction between industry leader dummies (based on sales revenue or total assets) and signed insider trading intensity (*TradeInt*) are significantly positive, suggesting that insider trading filings by industry leaders have stronger information transfer effects on their industry peers. Depending on the size definition we use, we find the magnitude of the information transfer effect increases from 160% to 210% for filings from industry leaders relative to non-leaders, suggesting that signals from industry leaders have much stronger impact than signals from non-leader firms.

To examine whether the incremental leader effects differ between purchases and sales filings, we run regressions separately by purchases and sales and find that the interaction term is significantly positive for sales (purchases) when leader dummy is defined based on sales revenue (total assets), suggesting that both insider purchases filings and sales filings could be informative to industry peers when they are from industry leaders.

3.4 DIFFERENTIAL INFORMATION TRANSFER EFFECTS ON RIVAL FIRMS VS. NON-RIVAL FIRMS

Kim et al. [2008] find that rival firms experience negative information transfer while non-rival firms experience positive information transfer in the management forecast setting. Capitalizing on this insight, we examine whether rival firms experience less positive information transfer than non-rival firms in the setting of insider trading filings. Based on prior information transfer research, we create two indicator variables for whether firms are rivals or non-rivals.

These indicators are observed information spillover effects in the settings of earnings announcements and industry-adjusted ROE correlation. We include the interactions between rival indicator variables and the signed insider trading intensity (*TradeInt*) in our main regressions and rely on the coefficients on these interactions to interpret the differential effects on rival firms vs. non-rival firms.

[Insert Table 5 here]

The results are provided in Table 5. As before, control variables generally show expected sign and significance. More importantly, we find that the coefficients on the signed insider trading intensity (*TradeInt*) are significantly positive while the coefficients on the interaction between the rival dummies (based on earnings announcements in model 1 and industry-adjusted ROE correlations in model 4) and the signed insider trading intensity are significantly negative, suggesting that non-rival firms experience positive information transfer while rival firms have less positive information transfers. Examining the effect of the rival dummies further, we find that the sum of the coefficients on the signed insider trading intensity and the coefficients on the interaction terms are insignificant. This implies that, for rival firms, the effects of competition mitigate the effects of industry commonalities such that the net effects of information transfer for rival firms are insignificant.

We run the regressions separately by purchases and sales and find the results are driven by sales sample, as shown in model 2 and 3 for rival dummy based on earnings announcements and in model 5 and 6 for rival dummy based on industry-adjusted ROE correlations, implying that the competition shifts exist only when rivals experience bad news in the insider trading filing setting.

3.5 DO INSIDER TRADING FILINGS PREDICT INDUSTRY PEERS' FUTURE EARNINGS ANNOUNCEMENT NEWS?

Our results so far indicate that, at least for insider sales, the disclosure of insider trades has an information transfer effect: peer firms' stock returns react negatively to the revelation of insider selling. In this section we investigate the actual news content of insider trading filings by documenting an association between insider trading filings and future industry news. We do this by regressing future earnings announcement news for peer firms (proxied by the cumulative abnormal returns of non-filing firms during the following earnings announcement period (*CAR_11EA*)) on the signed insider trading intensity (*TradeInt*). We expect a positive sign on the signed insider trading intensity, especially for the disclosures of insider sales.

[Insert Table 6 here]

The results are reported in Table 6. We find that signed insider trading intensity (*TradeInt*) is significantly positively correlated with the following earnings announcement news of industry peers. When we separate the sample according to the sign of *TradeInt* (insider purchase filings or insider sales filings), we find that insider purchase intensity is insignificantly correlated with future earnings announcement news while insider sales intensity (with a negative sign) is significantly positively correlated with future earnings announcement news. Thus, the incidence of insider selling at a given firm predicts future negative earnings news at peer firms. Overall, these findings support our conjecture that insider trading filings signal future industry performance and that this relation is stronger for insider sales than for insider purchases, consistent with our prior findings.

4. Additional Analyses

4.1 INSIDER TRADING AND INDUSTRY MISVALUATION

To further investigate whether insiders trade on industry-level information, we examine whether insiders more likely purchase (sell) when an industry is under-(over-) valued estimated based on the methodology of Rhodes-Kropf et al. [2005].

Rhodes-Kropf et al. [2005] models a firm's market value as a function of book value, net income, and leverage. They estimate three models with increasingly comprehensive determinants of market value as listed below:

Model 1: $log(MV)_{i,t}=\alpha_{j,t}+\beta_1 log(BV)_{i,t}+\varepsilon_{i,t}.$ (5)

Model 2: $log(MV)_{i,t}=\alpha_{j,t}+\beta_1 log(BV)_{i,t}+\beta_2 log(abs(NI))_{i,t} +\beta_3 NegDum(NI)_{i,t}*log(abs(NI))_{i,t} + \varepsilon_{i,t}$ (6)

Model 3: $log(MV)_{i,t}=\alpha_{j,t}+\beta_1 log(BV)_{i,t}+\beta_2 log(abs(NI))_{i,t}+\beta_3 NegDum(NI)_{i,t}*log(abs(NI))_{i,t} +\beta_4 Lev_{i,t} + \varepsilon_{i,t}$ (7)

where:

MV = market capitalization at the end of fiscal year;

BV = book value at the end of fiscal year;

NI = net income before extraordinary items for the fiscal year, and

abs(NI) = the absolute value of NI;

NegDum(NI) = an indicator variable that takes the value of one if net income before extraordinary items is negative and zero otherwise;

Lev = firm leverage (the ratio of long-term liabilities to total assets).

We run each model by industry (four-digit SIC code)-year and obtain the industry-year-level valuation multiples, i.e., the intercept and the coefficients for each accounting information variable. Applying industry-year multiples together with firm-specific accounting information variables gives us the valuation estimates based on industry-year-level multiples. Then we calculate the industry-level multiples as the average (across years) of industry-year-level multiples by industry. Plugging in firm-specific accounting information variables in models with industry-level multiples yields the valuation estimates based on industry-level multiples. Industry misvaluation equals the difference between the valuation based on industry-year-level multiples and the valuation based on the industry-level multiples.[9]

[Insert Table 7 here]

To test whether insiders trade on industry-level news, we first separate the sample according to the rank of industry misvaluation based on three models into three groups (more overvalued as rank increases), and then calculate the average insider purchase, average insider sales and average net trades for each group. The results are provided in Panel A of Table 7. There are 66,957 firm-year observations in the aggregated insider trading sample. We can see that as industry misvaluation increases, both insider sales and net trades increases, while insider

[9] Rhodes-Kropf et al. [2005] also estimate a firm-year misvaluation measure and a long-run value to book measure; the former estimates how over or under-valued a firm is in a given year while the latter measures the component of the market-to-book ratio that is consistent with the firm's fundamentals and the long-run relation between fundamentals and market value. See sections 4 and 5 of Rhodes-Kropf et al. [2005] for details on the estimation of these measures.

purchases not necessarily decreases, especially when industry misvaluation is measured based on model 2 and 3, suggesting that insiders more likely trade on negative industry-level news but not positive industry-level news.

We then look at this issue reversely by first grouping the observations based on insider trades (purchases vs. sales) first and then calculating the average industry misvaluation. Specially, we aggregate the insider trading data at the firm-year level and separate the sample according to whether the aggregate number of shares traded is positive (net insider purchasing during the firm-year) or negative (net insider selling during the firm-year). We then calculate industry-year misvaluation for firm-years with net purchasing and firm-years with net selling. Based on the results discussed before, we expect that firm-years with net insider purchasing (net insider selling) occur when the firm's industry is under (over) valued and further, this relation between industry misvaluation and firm-year trading to be stronger for firm-years with net insider selling. Panel B provides the results. In the net purchase subsample, average industry misvaluation from Model 1 is negative (signifying undervaluation) but only marginally significant. Using Models 2 and 3 there is no significant industry-level misvaluation for firms with net insider purchasing. In contrast, firm-years with net insider selling are in industries that are significantly overvalued using all three valuation models. The differences between purchases and sales are significant across all three models. Thus, we find evidence that insider sales (but not purchases) are associated with industry-level misvaluation, in line with prior evidence.

Panel C presents similar findings in a regression setting. This panel reports the OLS coefficient (with t-statistics in parentheses) on the industry-level misvaluation measure in regressions with measures of insider trading as the dependent variable. Specifically, we regress insider purchases (scaled by shares outstanding), insider sales (scaled by shares outstanding), and net insider trading (purchases minus sales, scaled by shares outstanding) on the Rhodes-Kropf et al. [200]) industry misvaluation measure, firm-level misvaluation measure, and long-run value to book value (for brevity, we only report the coefficient on industry misvaluation). As seen in Panel C, the coefficients on industry misvaluation are insignificant in explaining insider purchases but is highly significant in explaining insider sales and net insider trading: when industries are overvalued, insider selling is higher and net insider trading is lower, i.e., insiders sell when their industries are overvalued.

4.2 EFFECTS OF INSIDER TRADING ON INDUSTRY-LEVEL INFORMATION

Our results thus far show that a firm's disclosure of insider trades provides incremental information to other firms in the same industry and that disclosures of insider sales contain more industry-level information than disclosures of insider purchases. In this section, we provide evidence based on an industry-level sample to show that insider trading, especially insider sales, helps prices incorporate industry-level information.

We first run the following regression for each four-digit industry and year:

$$INDRET_{i,t}=\alpha_{j,t}+\beta_1 MARET_{i,t}+\beta_2 MARET_{i,t-1}+\varepsilon_{i,t} \quad (8)$$

where

INDRET = the four-digit SIC industry value-weighted weekly return;

MARET = the value-weighted market weekly return.

The R^2 obtained in model (8) represents how much of the variation in industry returns can be explained by the market return. Correspondingly, we use $\log((1- R^2)/R^2)$ (*INDR2*) as a measure of the relative importance of industry specific information. We use the following empirical specification to test the impact of insider trading on the industry information in industry prices at the four-digit SIC industry level:

$$INDR2 = \alpha+\beta_1 Trade+\beta_2 HERF+\beta_3 NIND+\beta_4 RETCORR+ \varepsilon \tag{9}$$

Insider trading activities (*Trade*) are industry-level aggregations of our firm-level measures of insider trading:

Trade_net = the absolute value of the difference between total shares purchased by insiders and total shares sold by insiders as a fraction of annual trading volume,

Trade_pur = total shares purchased by insiders as a fraction of annual trading volume,

Trade_sal = total shares sold by insiders as a fraction of annual trading volume;

HERF = the revenue-based Herfindahl index of industry-level concentration;

NIND = the average number of firms used to calculate the weekly industry return index;

RETCORR = the Spearman correlation between *MARET* and *INDRET* for each industry year;

[Insert Table 8 here]

The results are shown in Table 8. Consistent with our conjecture, insider trading activities at the industry level significantly increase the industry-specific information in prices. This relation is driven by insider sales with the coefficient on insider purchase being insignificantly different from zero and significantly different from the coefficient on insider sales.

5. Conclusion

In this paper, we examine whether insider trading filings have intra-industry information transfer effects. We find that insider trading filings convey industry-level information and investors of industry peers learn from the signal of the filings and react to the signal in the same direction. The information transfer effects differ across firms in the same industry. Insider trading filings from industry leaders have stronger information transfer effects to industry peers, suggesting filings from industry leaders contain more industry-level information. We also find that rival firms experience less positive information transfer effects than non-rival firms, consistent with the argument that industry commonalities and competitive shifts explain the effects of information transfer in opposite directions. Furthermore, we show that insider selling is associated with an accounting-based measure of industry overvaluation; however, insider purchases are not associated with industry undervaluation. Similarly, insider selling (but not insider purchasing) is positively associated with how idiosyncratic an industry's returns are. Overall, our results show that insider selling is strongly associated with industry information. We speculate that this is due to negative shocks being more systematic than positive shocks, lower litigation risk for insider sales based on industry-level information relative to that based on firm-specific information, and large equity position of insiders.

Previous studies on insider trading find that insider trading filings have significant impacts on a firm's stock return (e.g., Brochet [2010] and Veenman [2012]). Our paper adds to this literature by showing that insider trading filings also affect the share price of industry peers. Our evidence shows that insider trading contains industry-level information in addition to the firm-specific information emphasized in prior papers such as Piotroski and Roulstone [2004]. The information transfer literature finds that earnings announcements and management forecasts have spillover effects on industry peers (e.g., Foster [1981], Baginski [1987], Han and Wild

[1990], and Kim et al. [2008]). Our paper contributes to this line of literature by providing evidence that insider trading filings can also convey industry information to investors.

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TABLE 1
Descriptive Statistics

Variable	Mean	Q1	Median	Q3	Std. Dev.
CAR02 (%)	-0.127	-2.445	-0.269	1.959	5.428
TradeInt (%)	-0.065	-0.055	-0.010	0.005	0.275
Size	1,877.014	62.401	177.475	625.367	11,821.390
BM	0.532	0.345	0.560	0.835	21.987
CAR_17 (%)	-0.082	-3.853	-0.496	2.957	10.029
LeaderDum1 (indicator)	0.124	0.000	0.000	0.000	0.330
LeaderDum2 (indicator)	0.163	0.000	0.000	0.000	0.369
RivalDum1 (indicator)	0.026	0.000	0.000	0.000	0.160
RivalDum2 (indicator)	0.001	0.000	0.000	0.000	0.035
CAR_11EA (%)	-0.132	-3.441	-0.173	3.204	7.921

The table provides descriptive statistics for the sample of 24,799,150 observations from 1986 to 2010. *CAR02* is the three-day cumulative abnormal return starting on a Form 4 filing date for non-filing firms matched based on four-digit SIC code, adjusted for the Fama-French size and book-to-market 5*5 portfolios. *TradeInt* is the number of shares as reported on Form 4's filed by insiders scaled by shares outstanding with positive sign for purchases and negative sign for sales. *Size* is the market capitalization at the beginning of a year in millions dollars. *BM* is the ratio of book value of equity on market capitalization at the beginning of a year. *CAR_17* is the seven-day cumulative abnormal returns prior to the Form 4 filing date for non-filing firms matched based on four-digit SIC code, adjusted for the Fama-French size and book-to-market 5*5 portfolios. *LeaderDum1* is an indicator variable that takes the value of one if total sale revenues is in the top decile of the Compustat population in that year and zero otherwise. *LeaderDum2* is an indicator variable that takes the value of one if the total assets is in the top decile of the Compustat population in that year and zero otherwise. *RivalDum1* is an indicator variable that takes the value of one if β_{UEA} is less than the first quartile of the population for both sides of competitors and zero otherwise, where β_{UEA} is the coefficient on unexpected earnings, defined as the difference between actual EPS and analyst forecast EPS scaled by the share price 21 days before the announcement, in the regression with dependent variable of non-announcing firms' three-day abnormal return starting on an earnings announcement date of announcing firms and control variables including *SIZE*, *BM*, and *CAR_17* for non-announcing firms in the whole sample period. *RivalDum2* is an indicator variable that takes the value of one if the industry-adjusted return on equity correlation between non-filing firms and filing firms in the past ten years is below the first quartile of the population for two sides of competitors and zero otherwise. *CAR_11EA* is the three-day cumulative abnormal starting on one day before earnings announcement date followed after the insider filings for non-filing firms matched based on four-digit SIC code, adjusted for the Fama-French size and book-to-market 5*5 portfolios. Additional data requirement on earnings announcement date and analyst forecast data reduce the sample size of *CAR_11EA* to 15,978,747. *TradeInt*, *CAR02*, *CAR_17* and *CAR02EA* are multiplied by 100 for exposition purpose.

TABLE 2

Pearson (upper diagonal) and Spearman (lower diagonal) correlation coefficients for select variables

	CAR02	TradeInt	log(Size)	log(BM)	CAR_17	Leader Dum1	Leader Dum2	RivalD um1	RivalD um2	CAR_11 UEA
CAR02		0.009	0.011	0.005	-0.075	0.000	0.001	0.003	0.001	0.028
TradeInt	0.010		0.038	0.096	-0.007	0.025	0.038	0.004	0.004	0.002
log(Size)	0.036	0.020		-0.275	0.006	-0.030	-0.035	0.077	0.005	0.029
log(BM)	0.004	0.146	-0.322		-0.008	-0.052	-0.020	-0.036	*0.000*	-0.002
CAR_17	-0.056	0.003	0.061	-0.008		0.003	0.002	0.003	*0.000*	0.000
LeaderDum1	-0.003	-0.033	-0.028	-0.056	-0.004		0.707	0.020	-0.001	0.001
LeaderDum2	*0.000*	-0.016	-0.033	-0.016	-0.001	0.707		0.026	-0.002	0.003
RivalDum1	0.006	-0.017	0.081	-0.045	0.008	0.020	0.026		0.003	0.006
RivalDum2	0.001	0.003	0.006	0.001	0.001	-0.001	-0.002	0.003		0.001
CAR_11UEA	0.026	0.007	0.043	0.001	0.006	-0.001	0.001	0.007	0.002	

The table provides the correlation matrix for the sample of 24,799,150 observations from 1986 to 2010. All variables are defined in Table 1. All correlation coefficients are significant at 1%-level except those in italics.

Table 3

Regressions of Non-filing Firms' Market Reaction on the Insider Trading Intensity of Filings Firms

$CAR02=\alpha+\beta_1 TradeInt+\beta_2 log(Size)+\beta_3 log(BM)+\beta_4 CAR\_17+\varepsilon$

Variable	All	Purchases	Sales	Difference
Panel A: Individual filings with full sample				
	Model 1	Model 2	Model 3	
TradeInt	0.141**	0.035	0.185***	-0.150*
	(2.53)	(0.62)	(3.09)	(-1.82)
log(Size)	0.038***	0.055***	0.030***	0.026***
	(8.78)	(6.76)	(7.31)	(3.40)
log(BM)	0.038**	-0.011	0.055***	-0.066***
	(2.13)	(-0.50)	(3.06)	(-3.54)
CAR_17	-0.041***	-0.050***	-0.037***	-0.014***
	(-21.64)	(-19.22)	(-19.69)	(-6.22)
Intercept	-0.830***	-1.204***	-0.628***	-0.628***
	(-10.03)	(-8.23)	(-7.74)	(-7.74)
Adjusted R^2	0.58%	0.81%	0.50%	
F-statistic	162.37***	104.71***	166.33***	
Sample Size	24,799,150	8,482,138	16,317,012	
Panel B: Excluding filings by routine traders				
	Model 4	Model 5	Model 6	
TradeInt	0.143**	0.049	0.184***	-0.135*
	(2.56)	(0.90)	(3.10)	(-1.68)
log(Size)	0.039***	0.056***	0.030***	0.026***
	(8.72)	(6.83)	(7.16)	(3.45)
log(BM)	0.039**	-0.010	0.057***	-0.067***
	(2.14)	(-0.48)	(3.03)	(-3.56)
CAR_17	-0.041***	-0.050***	-0.037***	-0.014***
	(-21.44)	(-19.35)	(-19.29)	(-6.16)
Intercept	-0.837***	-1.219***	-0.631***	-0.631***
	(-9.92)	(-8.28)	(-7.56)	(-7.56)
Adjusted R^2	0.59%	0.81%	0.51%	
F-statistic	162.44***	105.47***	164.36***	
Sample Size	23,665,972	8,189,508	15,476,464	
Panel C: Aggregated filings				
	Model 7	Model 8	Model 9	
TradeInt	0.082*	-0.001	0.128**	-0.129
	(1.75)	(-0.01)	(2.40)	(-1.28)
log(Size)	0.047***	0.064***	0.040***	0.023***
	(19.98)	(13.93)	(15.09)	(4.59)
log(BM)	0.015*	-0.020	0.026***	-0.045***
	(1.90)	(-1.42)	(3.16)	(-3.26)
CAR_17	-0.051***	-0.062***	-0.048***	-0.014***
	(-35.45)	(-28.54)	(-32.59)	(-7.25)
Intercept	-1.010***	-1.374***	-0.847***	-0.847***
	(-21.69)	(-15.72)	(-15.75)	(-15.75)
Adjusted R^2	0.60%	0.84%	0.52%	
F-statistic	388.22***	221.51***	335.96***	
Sample Size	7,077,021	1,960,853	5,116,168	

The table provides regression results on the market reaction of non-filing firms matched based on based on four-digit SIC code to the insider trading intensity of filling firms based on the sample of 24,799,150 non-filing-firms-filing-date observations from 1986 to 2010. Panel A provides the results when insider trading intensity (*TradeInt*) is measured at individual filing level and full sample is used. Panel B presents the results based on the sample excluding filings by routine traders. Panel C reports the results when *TradeInt* is measured at industry level and is equal to the mean *TradeInt* in the same industry and date. All variables are defined in Table 1. The table reports

OLS coefficient estimates and (in parentheses) t-statistics based on robust standard errors that are clustered by date. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

TABLE 4

Incremental Information Transfer Effects for Filings from Industry Leaders

$CAR02=\alpha+\beta_1 TradeInt*LeaderDum+\beta_2 TradeInt+\beta_3 LeaderDum+\beta_4 log(Size)+\beta_5 log(BM)+\beta_6 CAR\_17+\varepsilon$

Variable	Leader dummy based on top decile sale revenue			Leader dummy based on top decile total assets		
	All	Purchases	Sales	All	Purchases	Sales
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
TradeInt *	0.269**	0.269	0.257*	0.209*	0.364*	0.194
LeaderDum (1)	(2.14)	(1.24)	(1.81)	(1.69)	(1.93)	(1.36)
	0.128**	0.026	0.174***	0.129**	0.020	0.174***
TradeInt (2)	(2.37)	(0.43)	(2.98)	(2.41)	(0.34)	(3.02)
	0.029**	0.032	0.012	0.034***	0.021	0.022
LeaderDum	(2.08)	(1.07)	(0.83)	(2.74)	(0.98)	(1.37)
	0.038***	0.055***	0.029***	0.038***	0.055***	0.029***
log(Size)	(8.75)	(6.79)	(7.16)	(8.82)	(6.79)	(7.27)
	0.038**	-0.010	0.055***	0.038**	-0.010	0.055***
log(BM)	(2.16)	(-0.47)	(3.08)	(2.14)	(-0.49)	(3.07)
	-0.041***	-0.050***	-0.037***	-0.041***	-0.050***	-0.037***
CAR_17	(-21.65)	(-19.22)	(-19.69)	(-21.66)	(-19.22)	(-19.70)
	-0.834***	-1.212***	-0.625***	-0.838***	-1.211***	-0.631***
Intercept	(-9.98)	(-8.25)	(-7.55)	(-10.14)	(-8.27)	(-7.75)
Adjusted R^2	0.58%	0.81%	0.51%	0.58%	0.81%	0.50%
F-statistic	120.47***	69.99***	116.57***	129.44***	71.31***	125.06***
Sample Size	24,799,150	8,482,138	16,317,012	24799150	8,482,138	16,317,012
Test: (1)+(2)	0.008	0.157	0.011	0.022	0.032	0.029

The table provides regression results for the testing of incremental information transfer effects for filings from industry leaders based on the sample of 24,799,150 non-filing-firms-filing-date observations from 1986 to 2010. All variables are defined in Table 1. The table reports OLS coefficient estimates and (in parentheses) t-statistics based on robust standard errors that are clustered by date. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

TABLE 5

Differential Information Transfer Effects on Rival Firms vs. Non-rival Firms

$CAR02=\alpha+\beta_1 TradeInt*RivalDum+\beta_2\ TradeInt+\beta_3 RivalDum+\beta_4 log(Size)+\beta_5 log(BM)+\beta_6 CAR\_17+\ \varepsilon$

Variable	Rival dummy based on earning announcement setting			Rival dummy based on ROE correlation		
	All	Purchases	Sales	All	Purchases	Sales
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
TradeInt * RivalDum (1)	-0.079*	0.091	-0.123**	-0.478**	-0.120	-0.738***
	(-1.67)	(0.57)	(-2.35)	(-2.00)	(-0.21)	(-2.67)
TradeInt (2)	0.142**	0.035	0.187***	0.141**	0.035	0.186***
	(2.54)	(0.62)	(3.10)	(2.53)	(0.63)	(3.09)
RivalDum	0.092***	0.084***	0.083***	0.077*	0.161**	-0.001
	(6.86)	(3.86)	(5.92)	(1.91)	(2.35)	(-0.03)
log(Size)	0.038***	0.055***	0.029***	0.038***	0.055***	0.030***
	(8.59)	(6.69)	(7.09)	(8.78)	(6.76)	(7.31)
log(BM)	0.038**	-0.010	0.055***	0.038**	-0.011	0.055***
	(2.14)	(-0.48)	(3.07)	(2.13)	(-0.50)	(3.06)
CAR_17	-0.041***	-0.050***	-0.037***	-0.041***	-0.050***	-0.037***
	(-21.65)	(-19.22)	(-19.69)	(-21.64)	(-19.22)	(-19.69)
Intercept	-0.821***	-1.197***	-0.618***	-0.830***	-1.204***	-0.628***
	(-9.86)	(-8.17)	(-7.56)	(-10.03)	(-8.23)	(-7.74)
Adjusted R^2	0.58%	0.81%	0.50%	0.58%	0.81%	0.50%
F-statistic	133.59***	77.24***	125.11***	111.68***	70.94***	113.23***
Sample Size	24,799,150	8,482,138	16,317,012	24799150	8,482,138	16,317,012
Test: (1)+(2)	0.323	0.451	0.350	0.155	0.882	0.044

The table provides regression results for the testing of differential information transfer effects on rival firms vs. non-rival firms based on the sample of 24,799,150 non-filing-firms-filing-date observations from 1986 to 2010. All variables are defined in Table 1. The table reports OLS coefficient estimates and (in parentheses) t-statistics based on robust standard errors that are clustered by date. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

TABLE 6

Do Insider Trading Filings Predict Industry Peers' Following Earnings Announcement News?

$CAR\_11EA = \alpha + \beta_1 TradeInt + \varepsilon$

Variable	All	Purchases	Sales
	Model 1	Model 2	Model 3
TradeInt	0.072***	0.057	0.072***
	(2.99)	(1.07)	(2.78)
Intercept	-0.127***	-0.125***	-0.128***
	(-11.28)	(-6.13)	(-12.94)
Adjusted R^2	596.2%	101.9%	676.3%
F-statistic	8.94***	1.15	7.74***
Sample Size	15,978,747	5,275,881	10,702,866

The table provides results on whether insider trading filings predict industry peers' following earnings announcement news based on the sample of 15,978,747 observations from 1986 to 2010. All variables are defined in Table 1. The table reports OLS coefficient estimates and (in parentheses) t-statistics based on robust standard errors that are clustered by date. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

TABLE 7

Industry Misvaluation and Insider Trading

Panel A: Average insider trading intensity based on industry misvaluation rank			
Rank	Trade_purch	Trade_sale	Trade_net
Rank based on model 1			
1	0.404	-0.770	-0.300
2	0.329	-0.903	-0.525
3	0.317	-1.015	-0.673
Rank based on model 2			
1	0.426	-0.795	-0.314
2	0.325	-0.988	-0.619
3	0.375	-1.073	-0.688
Rank based on model 3			
1	0.425	-0.818	-0.337
2	0.337	-0.983	-0.606
3	0.365	-1.057	-0.675
Panel B: Average industry misvaluation by net purchase versus net sales firm-year observations			
Variable	Purchases	Sales	Difference
Model 1	-0.030*	0.132***	-0.162***
	(-1.82)	(15.79)	(-8.75)
Model 2	-0.012	0.194***	-0.206***
	(-0.49)	(13.04)	(-7.17)
Model 3	0.023	0.209***	-0.186***
	(0.78)	(11.81)	(-5.38)
Panel C: Coefficients on industry misvaluation in regressions explaining insider-trading measures			
Variable	Purchases	Sales	Trade_net
Model 1	0.027	-0.455***	-0.471***
	(0.67)	(-11.91)	(-16.41)
Model 2	0.023	-0.395***	-0.471***
	(0.62)	(-11.16)	(-17.59)
Model 3	0.020	-0.368***	-0.452***
	(0.55)	(-10.55)	(-17.27)

The table examines whether insiders trade on industry misvaluation as proxied by the Rhodes-Kropf et al. (2005) market-to-book decomposition based on the sample of 66,957 firm-year observations from 1986 to 2010. Panel A presents the average insider trading intensity according to the industry misvaluation rank based on the three valuation models, i.e., model 1, 2, and 3. The insider-trading intensity measures include *Trade_purch*, *Trade_sale*, and *Trade_net*. *Trade_purch* is total shares purchased by insiders scaled by shares outstanding. *Trade_sale* is total shares sold by insiders scaled by shares outstanding. *Trade_net* is the total shares purchased by insiders minus the total shares sold by insiders scaled by shares outstanding. Models 1, 2, and 3 refer to the following three valuation regressions in Rhodes-Kropf et al. (2005):

Model 1: $log(MV)_{i,t}=\alpha_{j,t}+\beta_1 log(BV)_{i,t}+\varepsilon_{i,t.}$, and

Model 2: $log(MV)_{i,t}=\alpha_{j,t}+\beta_1 log(BV)_{i,t}+\beta_2 log(abs(NI))_{i,t} +\beta_3 NegDum(NI)_{i,t}*log(abs(NI))_{i,t}+ \varepsilon_{i,t.}$, and

Model 3: $log(MV)_{i,t}=\alpha_{j,t}+\beta_1 log(BV)_{i,t}+\beta_2 log(abs(NI))_{i,t}+\beta_3 NegDum(NI)_{i,t}*log(abs(NI))_{i,t}+\beta_4 Lev_{i,t}+\varepsilon_{i,t.}$,

where *MV* is market capitalization at the end of the fiscal year; *BV* is book value at the end of the fiscal year; *NI* is net income before extraordinary items for the fiscal year; *abs(NI)* is the absolute value of NI; *NegDum(NI)* is an indicator variable that takes the value of one if net income before extraordinary items is negative and zero otherwise; and *Lev* is the leverage ratio (the ratio of long-term liabilities to total assets). Each model is estimated cross-sectionally by industry-year where industry is defined by four-digit SIC. The valuation based on industry-year-level multiples equals to the firm-specific accounting information variables multiplied by the industry-year multiples. The valuation based on industry-level multiples equals the firm-specific accounting information variables multiplied by the industry-level multiples which are the average, across years, of the industry-year multiples; industry is defined by four-digit SIC. Industry misvaluation equals the difference between the valuation based on industry-year-level multiples and the valuation based on the industry-level multiples. Firm misvaluation equals to the difference between market value and the valuation based on industry-year-level multiples. Long-run value to book value equals the difference between the valuation based on industry-level multiples and the book value of equity.

Panel B provides the average industry misvaluation for firm-years with net insider purchases (column 1) and firm-years with net insider sales (column 2), as well as the difference between them (column 3).

Panel C reports OLS coefficient estimates (with t-statistics in parentheses based on standard errors clustered by firm) from a regression of insider trading measures on industry-level misvaluation, firm-level misvaluation, and long-run value to book value.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

TABLE 8

Effects of Insider Trading on Industry-level Information

$INDR2 = \alpha + \beta_1 Trade + \beta_2 log(HERF) + \beta_3 log(NIND) + \beta_4 RETCORR + \varepsilon$

	Model 1	Model 2	Model 3	Model 4
Trade_net	0.040*** (2.94)			
Trade_pur (1)		0.025 (1.30)	0.031 (1.58)	-0.009 (-0.59)
Trade_sal (2)		0.043*** (3.39)	0.052*** (4.11)	0.031*** (3.20)
log(HERF)			-0.058 (-1.43)	-0.021 (-0.76)
log(NIND)			-0.227*** (-6.93)	0.026 (1.18)
RETCORR				-4.283*** (-52.93)
Intercept	3.773*** (167.87)	3.696*** (93.68)	4.236*** (25.98)	5.101*** (11.97)
Fixed effects	Industry	Industry	Industry	Industry
Adjusted R^2	3.46%	3.51%	4.90%	34.21%
F-statistic	311.12***	229.28***	3105.73***	249.15***
Sample Size	7,183	7,183	7,183	7,183
Test: (1)-(2)		0.443	0.387	0.032

The table provides regression results on the effects of insider trading on the industry-level information based on the sample of 7,183 industry-year observations in the period between 1986 and 2010. The dependent variable is *INDR2*. *INDR2* is defined as $\log((1-R^2)/R^2)$, where R^2 is the R^2 obtained from the following regression:

$$INDRET_{i,t} = \alpha_{j,t} + \beta_1 MARET_{i,t} + \beta_2 MARET_{i,t-1} + \varepsilon_{i,t}.$$

where *MARET* is the value-weighted market return and *INDRET* is the four-digit SIC industry value-weighted return for week t. Insider trading is measured alternatively by *Trade_net*, *Trade_pur*, or *Trade_sal*. *Trade_net* is the absolute value of the difference between total shares purchased by insiders and total shares sold by insiders as a fraction of shares outstanding. *Trade_pur* is total shares purchased by insiders as a fraction of shares outstanding. *Trade_sal* is total shares sold by insiders as a fraction of shares outstanding. We use industry-year average values in the regressions. *HERF* is the revenue-based Herfindahl index of industry-level concentration. *NIND* is the average number of firms used to calculate the weekly industry return index. *RETCORR* is the Spearman correlation between *MARET* and *INDRET* for each industry year. The table reports OLS coefficient estimates and (in parentheses) t-statistics based on robust standard errors that are clustered by industry. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.