Decomposing Firms' Future Returns to Identify Information Driving Insiders' Trades

DAVID ABOODY, ELZABETH GUTIERREZ, RUIHAO KE, and JOHN HUGHES*

May 13, 2014

ABSTRACT

By decomposing future firm returns into firm-specific, industry-specific, and economy-wide components, we investigate the information upon which insiders condition their trades. We find that insiders' trades are significantly associated with the firm-specific and economy-wide components of future firm excess returns. Having partitioned insider trades into purchases and sales and controlling for routine trades, we find that sales as well as purchases are significantly associated with these two components of future returns. The economy-wide component is especially prominent for insiders' sales, suggesting that a down market may provide a cover from liability. Further refining our classification of firms in the same industry by the geographic location of their headquarters, we find that insiders' sales are positively associated with an industry-specific component for firms having the same headquarter location, suggesting that insiders share bad news about future industry prospects.

*David Aboody and John Hughes are from the Anderson School of Management at UCLA; Elizabeth Gutierrez is from the School of Accounting, Florida International University; and Ruihao Ke is from the Cox School of Business, Southern Methodist University. We thank Gordon Phillips and Gerard Hoberg for generously providing us with their text-based industry classification data. We also thank Yu Hou, Lynn Li, Jing Liu, Bugra Ozel, Clare Wang, and the participants attending a faculty brown bag at Florida International University for helpful comments. All remaining deficiencies are the responsibility of the authors.

Decomposing Firms' Future Returns to Identify Information Driving Insiders' Trades

ABSTRACT

By decomposing future firm returns into firm-specific, industry-specific, and economy-wide components, we investigate the information upon which insiders condition their trades. We find that insiders' trades are significantly associated with the firm-specific and economy-wide components of future firm excess returns. Having partitioned insider trades into purchases and sales and controlling for routine trades, we find that sales as well as purchases are significantly associated with these two components of future returns. The economy-wide component is especially prominent for insiders' sales suggesting that a down market may provide a cover from liability. Further refining our classification of firms in the same industry by the geographic location of their headquarters, we find that insiders' sales are positively associated with an industry-specific component of future returns for firms having the same location suggesting that insiders share bad news about future industry prospects.

There is extensive evidence that corporate insiders profit from trades in their firms' shares consistent with exploiting private information about future firm prospects.[1] Furthermore, studies have found a significant association between aggregate insiders' trades and aggregate future market returns suggesting that insiders' information advantage extends to economy-wide shocks.[2] However, the literature has not yet distinguished the relative importance of firm-specific, industry-specific, and economy-wide components of information in conditioning insiders' trades in their firm's shares, nor has it given much attention to identifying an industry component to insiders' private

[1] Seyhun (1986) finds average risk-adjusted gains between 4.3% and 5.6% for stock purchasers and around 2% percent for sellers. A summary of the early research on insider trading can be found in Seyhun (1998). More recently, Jeng, Metrick, and Zeckhuser (2003) find abnormal returns of approximately 6% for purchases and insignificant abnormal returns for sales.

[2] See, Seyhun (1988, 1992), Chowdhury, Howe and Lin (1993), Lakonishok and Lee (2001), Jiang and Zaman (2010), and Andriosopoulos and Hoque (2011). We replicate the qualitative findings of Lakonishok and Lee (2001) as a check that market conditions are reasonably similar. Our results in this regard are available upon request.

information. We seek to address these issues by employing a decomposition of future firm returns to infer the components of information most prominent in driving insiders' trades.

While we expect firm-specific and economy-wide components of insiders' information to be significant drivers of insiders' trades, our decomposition and other features of our research design enable a closer look at the roles played by these components. In addition, notwithstanding the body of evidence that insiders profit from their trades on these components, there has been scant evidence that they profit from sales.[3] Part of the explanation is that insiders are often compensated through grants of stock options and restricted stock, suggesting that information-based trades are confounded by trades based on incentives to consume and diversify making it difficult to identify the former. We examine the separate effects of the components from our decomposition on insiders' purchases and sales after controlling for routine trades based on such incentives. We also partition the sample into single-segment and multi-segment firms as a measure of relative sensitivity to economy-wide shocks for which insiders are more likely to obtain economy-wide information. Although intended primarily for other purposes, further partitions based on product market leadership and price synchronicity may be viewed as likely indicants of a stronger role for economy-wide information. Our findings based on this research design offer new insights on insider trading, especially with respect to effects of private information on insiders' sales for firm-specific and economy-wide components.

Detecting the effects for an industry-specific component on insiders' trades requires further refinements in our design. *A priori*, it is difficult to gauge the relation

[3] See Jeng, Metrick, and Zeckhuser (2003).

between insiders' trades and an industry-specific component of their private information. A number of studies examine intra-industry information transfers by documenting the impact of firms' disclosures on rival firms' returns consistent with information events at the industry level for which insiders may acquire private information. However, we are unaware of any studies that have sought to directly link insiders' trades to an industry component of private information. In order to enhance the prospect of detecting an industry-specific component, we consider several industry classification systems including text-based methods. Our further refinements consider the greater potential for the exchange of information related to industry prospects among insiders of firms with common geographic headquarters locations and the influence of within industry product market power on the manner in which insiders may exploit private information. Notably, our findings, apart from the influence of product market power, establish previously unidentified associations between insider trades and an industry-specific component to their private information.

Our approach in decomposing future returns corresponds to Campbell, Lettau, Malkiel, and Xu's (2001) decomposition of the CAPM. Having decomposed firm excess returns into firm-specific, industry-specific, and economy-wide components, we regress our measure of firm-month insider trading (net insiders' purchase ratio) on these components while control for decomposed past excess returns. As mentioned, we employ a number of industry classification systems. These include the Standard Industrial Classification (SIC) 2-digit and 3-digit, the North American Industry Classification System (NAICS) 3-digit and 4-digit, Fama and French's (1997) 48 industries, and both Hoberg and Phillips' (2010) Text-based Network Industry Classification (TNIC) 3-digit and their Text-based Fixed Industry Classification (FIC) of 100 industries.[4] Among these systems, the text-based classifications of Hoberg and Phillips (2010) appear best posed for grouping product market competitors in order to implement the further refinements to identify the influence of industry-specific information on insiders' trades.

Along with sharpening the focus by distinguishing components of information that may be driving insiders' trades, we control for routine trades that are unlikely to be information-based by removing firm and year fixed effects and separating purchases and sales, given that incentives to consume or diversify may vary across those cases.[5] Similar in principle, Cohen, Malloy, and Pomorski (2012) tease out routine trades by examining past patterns of individual insiders trades.[6] The remaining trades, referred to as "opportunistic," are found to be profitable on the sell side as well as on the buy side. Supportive of Cohen, et al.'s (2012) results, we find that insiders appear to sell as well as buy, based on all three components of their private information inferred from our decomposition.[7] This finding is consistent with insiders' tending to time their sales co-incident with a down industry or down market possibly as cover from liability.

The literature on information sharing in industrial organizations offers a rationale for firms in the same industry to exchange information.[8] In turn, a common geographic

[4] Where possible, we employ classifications that reflect similar granularity for comparability. Since we employ classifications that reflect similar granularity for comparability and for brevity we do not include the results for 3-digit SIC code and 4 digit NAICS code. Our results are robust with respect to those two classifications.
[5] This is especially true as we observe different coefficients on the industry-specific and market-wide components.
[6] Aboody and Kasznik (2000) adopt a similar procedure by separating regularly timed option grants and relating other grants to the exploitation of private information through trades prior to the release of earnings announcements.
[7] Results for the industry-specific component are achieved in particular for insiders of firms with headquarters in the same geographic location.
[8] See Vives (1990) for a survey of the information sharing literature. More recently, Raith (2006) provides a unifying perspective on information sharing. Pae (2014) introduces spillovers of enabling knowledge from investments in demand enhancements as a friction that deters unravelling.

location of firms' headquarters suggests a conduit through which such information exchange might transpire. These observations suggest that more powerful tests for detecting an industry-specific component to insiders' information might be achieved by partitioning industries into groups of firms that either have or do not have common geographic headquarters locations. Similar to Prinski and Wang (2006), we identify such locations based on Metropolitan Statistical Area (MSA) as defined by the U.S. Census Bureau in 2009. Pirinsky and Wang (2006) suggest that information obtained from social and economic associations within MSAs influence investors' trading behavior as an explanation for correlated returns. Almazan, et. al. (2010) provides further support for industry information exchange by documenting a higher correlation of economic activities among firms' headquarters located within geographic clusters. Dougal, Parsons, and Titman (2012) find that insiders of firms in the same industry that belong to the same MSA may be more likely to coordinate by sharing information on investment opportunities. In keeping with these possibilities, our results are consistent with the presence of an industry-specific component to insiders' private information for firms having the same MSA.[9]

A very different perspective on the role an industry-specific component of private information on insiders' trades has been considered by Tookes (2008) in the context of product market competition. Empirically, using earnings announcements as a time of information asymmetry, she finds that lagged order flows and returns of non-announcing competitors are informative of announcing firms' returns. In her analysis, industry-wide

[9] Network theory may offer an alternative to MSA classifications as mechanism through which information might be exchanged among insiders. Such an approach is employed by Fracassi and Tate (2012) who use panel data on S&P 1500 companies to identify external network connections between directors and CEOs. They find that such network connections influence director selection and subsequent firm performance.

shocks have a greater effect on future returns of weaker firms with lower market share. This creates an incentive for insiders of stronger firms with greater market share to invest in competitor firms' stock as a way to more fully exploit information about such shocks. Enhancing this incentive are the fewer restrictions on trades in stocks other than insiders' own firm's stock. Accordingly, insiders of firms with larger market shares may be expected to trade less in their own firm's stock in favor of trades in competitors. Consistent with this view, our results suggest an inverse relation between insiders' trades and industry-specific information for insiders' purchases under the text-based industry classifications of Hoberg and Phillips (2010), arguably the system most attuned to capturing close competitors. However, undermining Tookes' explanation, we do not detect an influence of product market power on the role played by this component in insider trading.

We also consider whether there is an association between insider trades and price synchronicity as measured by Piotroski and Roulstone (2004). Their measure of price synchronicity is based on the relative explanatory power of regressions of firm returns on past market and industry returns. They then examine the relations between this measure and unsigned insiders' trades, changes in institutional holdings, and number of analysts' earnings forecasts and revisions. The idea is that high (low) price synchronicity is associated with relatively less (more) information conveyed through insider trading activity. In the context of our study, we expect and find stronger associations of insider trades with the economy-wide component of inferred private information when price synchronicity is higher. However, we do not find a significant association of insider trades with the industry-specific component but do find stronger associations of insider trades with the firm-specific component when price synchronicity is high, both of which run counter to the above predictions.

Conjecturing that insiders of firms with operations that straddle several industries are likely to have greater private information related to economy-wide shocks, we categorize firms by whether they are single-segment or multi-segment and test whether economy-wide information plays a larger role with insiders of the latter. We find that the influence of the economy-wide component is greater for multi-segment firms. Since the number of segments and firm size are positively correlated, it is possible that this partition might be capturing an effect of size *per se*. Both interpretations are reasonable as a basis for our conjecture.

Previous studies investigating characteristics of information that may be driving insider trades include Aboody and Lev (2000) on R&D intensity as an indicator of firms' more likely possessing private information; Ke, Huddart, and Petroni (2003) on insiders' trades as precursors to breaks in quarterly earnings announcements that suggest foreknowledge; Piotroski and Roulstone (2005) on insiders' trades as predictors of future earnings and book-to-market ratios; and Aboody and Kasznik (2000) on the timing of option grants relative to voluntary disclosure as a means for insiders to front-run the market on the content of those disclosures. Aboody, Hughes, Liu, and Su (2009) extend this line of research to the timing of the exercise of stock options and subsequent disposition of shares acquired. However, none of these studies attempts to decompose insiders' private information into distinct firm-specific, industry-specific, and economy-wide components. Note that we make a distinction between firm-level information, which could contain both industry-specific and economy-wide components, and firm-specific information which by construction is orthogonal to those two components.[10]

Summarizing the principal results, our findings of significance for the economy-wide component of insiders' private information refine previous findings of an association between aggregate insider trading and future market returns that did not distinguish between components of insiders' private information or between insiders' purchases and sales. Our findings on drivers of insiders' sales reinforce those of Cohen et al. (2012), with the added observation that both the firm-specific and economy-wide components of insiders' private information are ubiquitously significant drivers. Our findings, when we group firms in the same industry based on geographic location of their headquarters (MSA), suggest that the exchange of industry-specific information among insiders of firms having the same MSA plays a significant role as a driver of insiders' sales and thereby offers a different perspective on co-movements of returns than that provided by Prinski and Wang (2006). We also find weak evidence from the broader sample consistent with insiders' reducing purchases when industry-specific news is good, which is consistent with Tookes (2008). However, our findings from partitioning firms based on the Lerner Index as a measure of market power are contrary to her analysis. Last, our findings on the associations of insiders' trades and price synchronicity across components of private information are only partially consistent with predictions based on Piotroski and Roulstone (2004).

Remaining sections of this paper are organized as follows: Section I lays out our decomposition of firm returns and panel regressions, section II describes the various

[10] A similar distinction is made by Hughes, Liu, and Liu (2007) in characterizing firm-level signals as containing information on both idiosyncratic and systematic risks.

industry classification systems and sample partitions that we employ, section III sets forth our sampling rules and descriptive statistics, section IV presents our empirical findings, and section V concludes.

I. Decomposition Procedure and Panel Regressions

In order to infer firm-specific, industry-specific, and economy-wide components of information driving insider trades, we decompose future firm returns in a three-step analysis that commences with running the following regressions every year with daily data for each industry and firm, respectively:

$$r_{i,t} = \beta_i r_{m,t} + \varepsilon_{i,t} \tag{1}$$

$$r_{f,t} = \beta_f r_{i,t} + \varepsilon_{f,t} \tag{2}$$

where, for industry i and/or firm f and day t, $r_{i,t}$ is the value-weighted industry excess return, $r_{m,t}$ is the value-weighted market excess return, $r_{f,t}$ is the firm excess return.

In the next step, we use betas estimated from (1) and (2) for each year y to estimate monthly residual returns:

$$\hat{\varepsilon}_{i,t} = r_{i,t} - \hat{\beta}_{i,y} r_{m,t} \tag{3}$$

$$\hat{\varepsilon}_{f,t} = r_{i,t} - \hat{\beta}_{f,y} r_{m,t}, \tag{4}$$

where for industry i, firm f , and month t, $r_{i,t}$ is the value-weighted industry excess return, $r_{m,t}$ is the value-weighted market excess return, and $r_{f,t}$ is the firm excess return.

Last, we estimate the firm-specific component of firm monthly excess returns by employing estimates of betas from regressions (1) and (2) above:

$$r_{f,t}^{fs} = r_{f,t} - \hat{\beta}_f \hat{\beta}_i r_{m,t} - \hat{\beta}_f \hat{\varepsilon}_{i,t}. \tag{5}$$

In summary, for firm *f* and month *t*, $r_{f,t}^{fs}$ is the firm-specific component, $r_{f,t}^{ew} = \hat{\beta}_f \hat{\beta}_i r_{m,t}$ is the economy-wide component, and $r_{f,t}^{is} = \hat{\beta}_f \hat{\varepsilon}_{i,t}$ is the industry-specific component of firm returns.

We then run a series of panel regressions of our measure of insider trading at the firm level, $npr_{f,t}$ on the components of future returns to infer the relative importance of each component as drivers of insider trading according to the following specification:

$$npr_{f,t} = \alpha + \beta_1 r_{f,t+1,t+6}^{fs} + \beta_2 r_{f,t+1,t+6}^{is} + \beta_3 r_{f,t+1,t+6}^{ew}$$
$$+\beta_4 r_{f,t-23,t}^{fs} + \beta_5 r_{f,t-23,t}^{is} + \beta_6 r_{f,t-23,t}^{ew} + \varepsilon_{f,t}, \quad (6)$$

where, for firm *f* and month *t*, $npr_{f,t}$ is the net purchase ratio, $r_{f,t+1,t+6}^{fs}$ is the future six-month firm-specific component of excess return, $r_{f,t-23,t}^{fs}$ is the past 24-month firm-specific component of raw return, $r_{f,t+1,t+6}^{is}$ is the future six-month industry-specific component of excess return, $r_{f,t-23,t}^{is}$ is the past 24-month industry-specific component of raw return, $r_{f,t+1,t+6}^{ew}$ is the future six-months economy-wide component excess return, and $r_{f,t-23,t}^{ew}$ is the past 24-month economy-wide component raw return.

As noted earlier, we employ various industry classification systems at different levels of granularity in estimating equations (1) and (2). In the next section, we describe several ways in which we cut the data when running the panel regressions specified by equation (6).

II. Industry Classifications and Further Sampling Partitions

As mentioned earlier, we employ several industry classification systems. The SIC and NAICS systems are generally well known. Another common classification is Fama and French's (1997) grouping of SIC-4 (digit) categories into 48 industries compared to 62 SIC-2 categories for our sample. The more recent NAICS-3 system has 76 categories for our sample. Recently, Hoberg and Phillips (2010) developed two new text-based classification systems (TNIC-3 and FIC100) based on product descriptions within annual 10K filings. These systems appear especially appropriate for identifying firms for which insiders are likely to exchange industry information. For TNIC-3, each firm has its own set of peers (industry) that evolves over time and that does not require transitivity. A firm's industry consists of those "peers" that are the closest determined by a threshold expressible as a percentage of firm pairs such that both firms are in the same industry. Transitivity and membership over fixed time periods is required for FIC100 which is fairly comparable in granularity to the SIC-2 and NAICS-3 systems. The TNIC system has as many "industries" as firms. In our study, we use TNIC-3, which has similar granularity to that of SIC-3 and NAICS-4-Digit.[11] While Holberg and Phillip's systems may have an advantage in detecting industry-specific effects, the data for these systems are available only from 1996-2008, which implies weaker statistical power.[12]

In identifying common headquarters locations, we use COMPUSTAT to obtain the state and county of a firm's headquarters. This location is matched to an MSA based on the 2009 delineations defined by the U.S. Census Bureau. An MSA consists of a core area that contains a substantial population nucleus and adjacent communities that have a high degree of social and economic integration with the core. MSAs may contain one or more counties that sometimes extend over state boundaries. Having grouped firms by both industry and MSA before applying our decomposition procedure, we are able to

[11] We thank Hoberg and Phillips for sharing their data with us.
[12] We also consider SIC 3-digit and NAICS 4-digit classifications for comparability with TNIC- 3.

capture an industry-specific information effect. As noted earlier, Pirinsky and Wang (2006) document co-movement of stock prices of firms within MSAs. They suggest that the co-movement is driven not by fundamentals but rather by trading patterns of individual investors in small firms. Our inquiry considers whether the sharing of information by insiders of firms in the same industry and headquartered in the same MSA is a contributing factor.

We use the Lerner Index, defined as the firm's percentage of operating profit margin, as a measure of product market power that we assume to be related to market share. Using COMPUSTAT data, the index is calculated as follows[13]:

$$\text{Lerner Index} = \frac{\text{Sales} - \text{Cost of Goods Sold} - \text{Selling, General and Administrative Expenses}}{\text{Sales}}$$

Following Gaspar and Massa (2005) and Peress (2010), we subtract the industry average Lerner Index to control for structural differences across industries unrelated to the degree of competition. In effect, the Lerner Index captures a firm's ability to price goods above marginal cost. A larger price-cost margin indicates stronger product market power (weaker competition). Based on this index, we partition firms into low, medium, and high market power categories.

We measure a firm's price synchronicity following a procedure similar to that of Piotroski and Roulstone (2004). For each firm-year observation, we run the following regression:

$$r_{f,t} = \alpha + \beta_1 r_{m,t-1} + \beta_2 r_{m,t} + \beta_3 r_{i,t-1} + \beta_4 r_{i,t} + \varepsilon_{f,t}$$

[13] If Cost of Goods Sold (data item #41) and Selling, General and Administrative Expenses (data item #189) are missing, we use Operating Income (data item #178).

where $r_{f,t}$ is firm *f*'s return in week *t*, $r_{m,t}$ is the value-weighted market return in week *t*, and $r_{i,t}$ is the value-weighted industry return excluding the firm in week *t*. We estimated this regression for each firm-year with a minimum of 20 weekly observations, for which a weekly return is defined as the compounded return over a minimum of four trading days during the week. Price synchronicity is then defined as $\log(R^2/(1–R^2))$, where R^2 is the coefficient of determination from the estimation of the above regression. By construction, high values indicate firms whose stock returns are closely tied to, i.e. vary strongly with, market and industry returns, and are assumed to reflect relatively less firm-specific information. Using this measure, we again, partition firms within the same industry into low, medium, and high price synchronicity categories.

III. Sampling Rules and Descriptive Statistics

Our sample universe includes data from 1987 to 2012. The firm-year database is constructed by merging the 10-K database with COMPUSTAT and the Center for Research in Security Prices (CRSP) database using the central index key (CIK), which is the primary key used by the SEC to identify the issuer. It includes all publicly traded firms (domestic firms traded on NYSE, AMEX, or NASDAQ) for which there are COMPUSTAT and CRSP data from 1987 to 2012. For Hoberg-Phillips' (2010) systems we use data from their Industry Classification Data Library from 1998-2008.[14]

We obtain insider trading data inclusive of all open market purchases and sales by labeled corporate insiders from Thompson Financial from 1987 to 2012. Insiders included in our sample are officers and directors of the firms classified by Thompson

[14] Industry classifications are based on web crawling and text parsing algorithms that process the text in the business descriptions of 10-K annual filings on the SEC Edgar website from 1996 to 2008. The database can be found at http://alex2.umd.edu/industrydata/industryclass.htm.

Financial as Levels 1 and 2 insiders. Insiders' transactions are required to satisfy the following conditions: (1) considered reliable by Thomson Financial;[15] (2) classified as open market purchases (transaction code "P") or open market sales ("S");[16] (3) involve 100 or more shares; (4) reported transaction price deviates by less than 20% of the closing price reported by CRSP on the same transaction day; and (5) reported number of shares traded is less than 20% of the shares outstanding as reported by CRSP. For each firm-month, we calculate both the total number of purchases and the total number of sales by the firms' insiders. Our initial measure of insider trading allows either net purchases or net sales to characterize trades. We then partition firm-month observations into net purchases or net sales.

Table I presents descriptive statistics for our entire sample that are not specific to any industry classification employed. As reported in Panel A, the percentage of firms where insiders trade at least once during the calendar year is approximately 51% for insider purchases and 57% for insider sales. Consistent with prior literature, the fraction of firms with insider sales is higher across the entire distribution than the fraction of firms with insider purchases. We next present the average annual number of trades per company of our sample firms. The number is calculated as the average of the number of total insider transactions divided by number of years. On average, the annual number of purchase transactions per firm is 0.56, with a standard deviation of 2.09, compared with 1.55 and a standard deviation of 9.57 for sale transactions. Similarly, both the dollar value of sale transactions and the dollar value as a percentage of market value are larger

[15] Reliable transactions are those whose cleanse code is one of the following, "R", "H", "L", "Y", "I", or "C".

[16] We also conduct analyses that include option exercises (transaction codes "X" and "M") with qualitatively similar results.

than the purchase transactions. Finally, consistent with sale transactions' being more frequent than purchase transactions, our measure of insider trading, *npr*, is negative for both the mean and median. Interestingly, for the vast majority of firms, insiders as a group trade in one direction, e.g., the group might purchase shares or sell shares during a given month.

(Insert Table I About Here)

In Panel B, we provide descriptive statistics for the dependent variables in our regressions using the SIC-2 sample as an example. As expected, the firm-specific past and future return components exhibit the larger standard deviations. Also, as expected, the mean (median) beta when regressing industry returns on the market, β_i, for our sample is 1.02 (1.0) as our sample encompasses almost all the firms in the CRSP database. The mean (median) beta from regressing firm returns on industry returns, β_f, is 0.58 (0.51), indicating that firm-specific returns are quite large in industry groupings. In other words, the fact that betas are substantially less than 1 implies that firm returns are not largely driven by industry shocks. The industry adjusted Lerner index mean and median are negative, indicating that for most industries there are dominant industry leaders. Finally, the price synchronicity is negative indicating that, for most firms, the R^2 from a regression of market and industry returns in firm-specific returns is regularly less than 0.5.

IV. Empirical Findings

A. Basic Findings

Table II present the results of regressing *npr*, our measure on insiders' trades by firm-month, on firm-specific ($r^{fs}_{f,t+1,t+6}$), industry-specific ($r^{is}_{f,t+1,t+6}$), and economy-wide

($r^{ew}_{f,t+1,t+6}$) components of future returns as proxies for information that may be driving insiders' trades in their firm's stock, with components of past returns serving as controls along with firm fixed effects. As noted earlier, the industry is alternatively defined by industry classifications based on SIC-2, FF48, NAICS-3, and Hoberg and Phillips' (2010) two definitions of industry TNIC-3 and FIC100.[17] Each panel reports the estimated coefficients and related t-statistics on the three components.

(Insert Table II About Here)

For the three industry classifications (SIC-2, FF48, NAICS-3), we estimate our regressions using the full sample period where insider trading is available: 1987 to 2012. The estimated coefficients for the future firm-specific returns are significantly positive and range from 0.062 to 0.063, with t-statistics ranging from 20.42 to 20.90. We find that the coefficients on future industry-specific returns are insignificant, while the coefficients on future economy-wide returns are significantly positive and range from 0.189 to .195, with t-statistics ranging from 6.97 to 7.08. At this juncture, the overall results indicate that insiders are basing their trades on economy-wide information, as well as firm-specific information, but not on their industry-specific information. Looking at the economic significance using SIC-2 as an example, we see that firm-specific information has a larger impact than does economy-wide information even though the economy-wide coefficient is larger. This is explained by the observation that the standard deviation of firm-specific returns is 0.324 compared to 0.087 for economy-wide returns. A one standard deviation change in firm-specific returns multiplied by the estimated coefficient translates to a 2% effect on insiders' trades for the firm-specific component compared to a 1.6% effect for the economy-wide component. These are sizeable effects, given that the

[17] We obtain similar results for SIC-3 and NAICS-4.

average monthly *npr* is -6%. For example, a one standard deviation change in future firm-specific returns implies a one-third deviation from average aggregate insider trades.

The results over the shorter time horizon for the economy-wide and firm-specific components, employing the Hoberg and Phillips' (2010) two definitions of industry, TNIC-3 and FIC100, are consistent with, although slightly weaker than, those of the previous three industry classifications. For both industry classifications the coefficient on the future economy-wide returns is significant with a coefficient of 0.246 and a t-statistic of 5.18 for the TNIC-3 classification and a coefficient of 0.248 and a t-statistic of 5.41 for the FIC100 classification. The decline in significance appears to be attributable to the significant drop in observations, as those industry classifications are available only from 1998 to 2008 and their sample includes fewer firms. Running the analysis employing SIC-2 and FF-48 over the same time frame yields similar significance levels. We note that, for TNIC-3, the coefficient on the industry-specific component is significantly negative, a result that we later consider may be driven by insiders' purchases.

Consistent with the literature documenting that insiders are contrarians, from Table II, we observe that the coefficient on the past 24 months' firm-specific component control is negative and highly significant for all industry classifications. New and more interesting is that insiders are strongly contrarian with respect to the industry-specific and market-wide components. One possibility is that insiders who trade on industry information are unaware of industry momentum as reported by Grinblatt and Moskowitz (1999). As such, following the time that their industries do well, insiders tend to sell their shares, notwithstanding that investors at large irrationally induce momentum into the industries that perform the best.

In Table III, we separate our sample into insiders' sales and purchases versus a benchmark of zero. Panel A contains results for insiders' purchases (*npr≥0*) and Panel B contains results for insiders' sales (*npr≤0*). For every industry classification and for both insiders' sales and purchases the estimated coefficients for the firm-specific component of information are significantly positive. Especially noteworthy is the highly significant role of firm-specific information for insiders' sales; indeed, sales are more highly responsive to this component than are purchases. These results stand in contrast to the generally weak prior evidence of insiders' exploiting private bad news, Cohen et al. (2012) being an exception. We attribute the stronger results to the combination of controlling for routine trades to consume and diversify through inclusion of firm and year fixed effects and our isolation of the information components that may be driving insiders' trades.

(Insert Table III About Here)

Table III demonstrates that Table II results of significantly positive effects of the economy-wide component of information are driven by both insiders' purchases and sales for all industry classifications. Specifically, for the SIC-2 industry classification the coefficients for the economy-wide component are 0.082 for purchases and 0.112 for sales with t-statistics of 3.66 and 4.19, respectively. Similarly, for FF48 and NAICS-3 industry classifications the coefficients of the economy-wide component for both insiders' purchases and sales are significantly positive. Regarding economic significance, again using SIC-2 as the benchmark, a one standard deviation change in economy-wide returns translates into a 0.7% change in insiders' purchases versus 1.0% in insiders' sales. Hence, our results consistently indicate that an increase in insiders' sales precedes economy-wide downturns and an increase in insiders' purchases precedes economy-wide upturns. Over all industry classifications, the economic significance of economy-wide information is notably greater for insiders' sales than for insiders' purchases. This suggests the likelihood that a down market may provide insiders with a cover from liability in exploiting bad news. Adding to our prior results of insiders' behaving as contrarian investors, we also observe that insiders' sales are more responsive to past returns than are purchases, lending support to the more prominent role of private information as a driver of sales than of purchases.

The same pattern, only stronger, emerges from the Hoberg and Phillips (2010) two industry classifications, TNIC-3 and FIC100. Specifically, the coefficients on the economy-wide component for insiders' purchases and sales under TNIC-3 are 0.081 and 0.168 with t-statistics of 1.96 and 3.84, respectively. Under FIC100, the coefficients are 0.090 and 0.161 with t-statistics of 2.22 and 3.71, respectively. Similar to the results of the previous classifications, the economic significance of insiders' sales is substantially greater (about double) than that of insiders' purchases, reinforcing the view that aggregate insiders' sales are more informative of future economy-wide returns. A further result based on the Hoberg and Phillips (2010) industry classifications is a significant negative association between insiders' purchases and the industry-specific information component for both FIC100 and TNIC-3. This suggests that insiders decrease (increase) purchases of their own company stocks when they observe good (bad) industry-specific information. These findings appear to be consistent with Tookes' (2008) prediction that insiders may have incentive to exploit industry-specific information through trade in the stock of their competitors rather than in the stock of their own firm. However, since our data are limited to trades by insiders in their own firms' shares, we cannot verify a reallocation to the stock of competitors. Moreover, later results, after partitioning by a measure of product market power, are inconsistent with Tookes' analysis.

B. Influence of Common Headquarters Location

Next, we consider the prospect that industry-specific information is advanced through common geographic locations of firm headquarters. For this analysis, we keep firms that are from the same industry with the same MSA. In Table IV, for all industry groupings, we report the results for firm-specific, industry-specific and economy-wide information components.[18] Our results are consistent across industry classifications. Similar to the results in Table II and III, we find that the firm-specific component of information continues to be significant. Comparing the coefficients in Table IV to those in Tables II and III, we draw similar inferences of economic significance with respect to the coefficient on economy-wide information. The coefficients on the economy-wide component of information are significantly positive and significant, with significance being driven by both insiders' purchases and sales. Furthermore, economic significance is greater for insiders' sales than for purchases reinforcing the view that insiders' purchases within an industry are not as informative as insiders' sales in predicting future economy-wide returns.

(Insert Table IV About Here)

In contrast to the results in Table II and III, the results in Table IV across industry classifications indicate that insiders of firms that share the same MSA as well as industry sell when their industry-specific information indicates bad news. Specifically, the

[18] Our analyses exclude TNIC. The intersection of TNIC and MSA yields too few observations to provide meaningful results.

coefficients on future industry-specific returns are significantly positive and, here, driven by insiders' sales and not purchases. We attribute the absence of the inverse association between insiders' purchases and the industry-specific component to the dominance of other information of common interest by firms sharing the same MSA as well as industry. Overall, the results in Table IV indicate that insiders of firms in the same MSA and industry consider firm-specific, industry-specific and economy-wide information when selling. Regarding economic significance, the economy-wide component dominates the industry-specific component by a factor of three to six, depending on the industry classification. Hence, given the same industry as well as MSA, our results indicate that insiders are responsive to economy-wide information but tend to regard the industry-specific information only when deciding whether to sell. These results with respect to the industry effect are consistent with insiders having an incentive to share information about impending low industry-wide demand in order to dissuade over production, but not information about high demand for which rival reactions might impinge on product market share.[19]

C. Influence of Product Market Power

To further investigate the effects of the industry-specific component on insiders' trades, we partition firms within industries by the Lerner Index as an indicator of product market power into low, medium, and high categories. As specified earlier, we measure market power by the Lerner index as the industry-adjusted percentage of the firm's operating profit margin. Table V, Panel A reports results based on the FIC100 industry

[19] As noted earlier, Pae (2014) shows how spillovers of enabling knowledge that allow rivals to free-ride on information pertaining to outcomes of investments in demand enhancements act as a friction resulting in high-end pooling such that only low demand information is shared.

classification and the results in Panel B are based on the TNIC-3 industry classification. Our results are separated into three groups from low to high market power for the entire sample, insider purchases and insider sales. Recall that a lower number for the Lerner index means that the firm has little control over price, consistent with customers' ability switch to an alternate product. In contrast, the lower the demand elasticity, the higher the market power as determined by the Lerner Index.

(Insert Table V About Here)

Two clear patterns emerge across industry classifications. First, insiders monotonically increase their reliance on firm-specific information with increases in the product market power of their firms, although the biggest jump occurs when moving from low market power to medium. For example, the full sample coefficient on the firm specific information for the FIC 100 industry groupings is 0.048 for the low market power, 0.093 for the medium market power, and 0.098 for the highest market power. Hence, insiders trade more aggressively when they have information and the firm is a market leader. Second, a similar pattern emerges for the economy-wide information. Continuing with the FIC100 industry classification as an example, the coefficient on the economy-wide information is 0.200 for the low market power, 0.275 for the medium market power, and 0.297 for the highest market power, all of which are highly significant. Here again, insiders in firms that are market leaders appear to trade more aggressively when they acquire economy-wide information. Regarding economic significance, both the coefficient on the economy-wide component and the standard deviation of returns increase with product market power, such that, the economic significance of that component within the high market power is higher than within the low power group.

Tookes' (2008) analysis suggests that informed traders of firms with greater market power may find it more advantageous to trade in the stock of competitors than in the stock of their own firms, in response to industry-wide information events. However, we find no evidence that this is the case. The inverse effect of industry-specific information on insiders' purchases is significant only for the high market power sub-sample under FIC100. The weaker evidence of such an effect by comparison with the earlier results reported in Table III may be attributable to the loss of statistical power. Nevertheless, the results from partitioning on the Lerner Index are not supportive of this aspect of Tookes' prediction.

D. Association with Price Synchronicity

In Table VI, we report results for the partitioning our sample by price synchronicity. We conjecture that high price synchronicity should be associated with a greater impact of economy-wide information on returns, strengthening the likelihood that insiders of firms exhibiting that synchronicity obtain such information and trade on it. Consistent with this conjecture, we observe that the coefficient on the economy-wide component monotonically increases with price synchronicity and that the coefficients are significantly larger (F-test of 5.18). Partitioning the sample of insiders' trades into sales and purchases, we find that, under high price synchronicity, the coefficient on the economy-wide component for insiders' sales is twice as large as that on insiders' purchases. Hence, greater price synchronicity between firms in the same industry implies greater predictability of future economy-wide downturns than upturns. In addition, although less definitive, for firms in the low price synchronicity group, insiders who receive information on a positive industry shock tend to increase their purchases, while insiders in firms that belong to the group of the high price synchronicity tend to act as contrarians to their industry-specific information and decrease their purchases.

(Insert Table VI About Here)

E. Sensitivity to Economy-wide Shocks

Last, we follow up on the notion that major firms such as industry leaders may have a stronger interest in acquiring information on the outlook for the economy as a whole that insiders might exploit. Table VII presents the results of partitioning our sample into single-segment and multi-segment firms as a proxy for their sensitivity to economy-wide shocks. We conjecture that multi-segment firms are exposed to a wider range of industries and, therefore, are more likely to acquire information on future prospects of the economy and assess the impact of those prospects on their firms. The evidence from Table VII suggests that this is the case; the effects of the economy-wide component of information on insiders' trades are significantly positive for multi-segment firms for all industry classifications and the coefficient in each case is significantly larger (F-test of 4.69) than for single segment firms. Consistent with our prior results, the coefficient on the economy-wide information component for multi-segment firms is significantly larger than for single segment firms for insiders' sales (F-test of 3.29), but is insignificantly different for both groups for insiders' purchases (F-test of 1.59). As noted earlier, the number of segments is correlated with firm size that also may be a factor in a firm's sensitivity to economy-wide shocks. We view the former as a measure of scope in the sense of lines of business that come under the firm's purview and the latter as a measure of scale in the sense of a firm's prominence in the economy. Not surprisingly, similar results are obtained after partitioning by size.

(Insert Table VII About Here)

V. Conclusion

Briefly summarizing, we decompose future firm excess returns into firm-specific, industry-specific, and economy-wide components to infer the types of private information upon which corporate insiders may be basing their trades. Estimated coefficients from regressions of net purchase ratios of aggregate insiders' trades on these future return components provide indications of the relative roles that firm-specific, industry-specific, and economy-wide information may play with respect to insiders' trading decisions.

Among the interesting results, we find that insiders appear to exploit bad firm-specific news on par with good news. We attribute improved detection of the effects of bad news on insiders' sales to our research design of controlling for firm and year fixed effects and the decomposition of future returns to infer types of information that may be driving insiders' trades. While previous studies report significant associations of aggregate insiders' trades and market returns, our decomposition enables us to isolate the effects of information on economy-wide shocks on this association. As expected, economy-wide information appears to play a large role in driving insiders' trades. Extending results from previous studies of aggregate insider trading, we find that the economic significance of economy-wide information on insiders' sales is generally greater than for insiders' purchases, possibly due to the cover that a down market provides in avoiding liability. We also find the economy-wide component to play a larger role for multi-segment firms more broadly exposed to economy-wide shocks, product market leaders, and for insiders of firms displaying higher price synchronicity.

Regarding the industry-specific component of information, we find that insiders of firms in the same industry and headquartered in the same MSA tend to sell when industry-specific news is bad, suggesting a greater predilection to share information about low future demand in order to preclude over production. For insiders' purchases from the broader sample, the evidence based text-based industry classifications suggests that insiders are reducing purchases in response to good industry-specific news possibly in order to reallocate holdings to competitors' shares. If data could be obtained regarding insiders' trades in shares of firms other than their own, then one could address our conjecture concerning tendencies to reallocate in this manner.

REFERENCES

Aboody David, John Hughes, Jing Liu and Wei Su, 2008, Are executive stock option exercises driven by private information? *Review of Accounting Studies* 13, 551-570.

Aboody, David, and Ron Kasznik, 2000, CEO stock option awards and the timing of corporate voluntary disclosures, *Journal of Accounting and Economics* 29, 73-100.

Aboody, David, and Baruch Lev, 2000, Information asymmetry, R&D, and insider gains, *Journal of Finance* 55, 2747-2766.

Almazan, Andres, Adolfo De Motta, Sheridan Titman, and Vahap Uysal, 2010, Financial structure, acquisition opportunities, and firm locations, *Journal of Finance* 65, 529-563.

Andriosopoulos, Dimitris, and Hafiz Hoque, 2011, Information content of aggregate and individual insider trading, Working paper.

Campbell, John Y., Martin Lettau, Burton G. Malkiel, and Yexiao Xu, 2001, Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk, *Journal of Finance* 56, 1-43.

Chowdhury, Mustafa, John S. Howe, and Ji-Chai Lin, 1993, The relation between aggregate insider transactions and stock market returns, *Journal of Financial and Quantitative Analysis* 28, 431-437.

Cohen, Lauren, Christopher Malloy, and Lukasz Pomorski, 2012, Decoding inside information, *Journal of Finance* 67, 1009-1043.

Dougal, Casey, Christopher Parsons, and Sheridan Titman, 2012, Urban vibrancy and corporate growth, Working paper.

Fama, Eugene F., and Kenneth R. French, 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153-193.

Fracassi, Cesare and Geoffrey Tate, 2012, External networking and internal firm goverance, *Journal of Finance* 67, 153-194.

Gaspar, José- Miguel, and Massimo Massa, 2005, Idiosyncratic volatility and product market competition, *Journal of Business* 79, 3125–3152.

Grinblatt, Mark, and Tobias Moskowitz, 1999, Do industries explain momentum?, *Journal of Finance* 54, 1249–1290

Hoberg, Gerard, and Gordon Phillips, 2010, Product market synergies and competition in mergers and acquisitions: A Text-Based Analysis. *Review of Financial Studies* 23, 3773-3811.

Hong, Harrison, Walter Torous, and Rossen Valkanov, 2007, Do industries lead stock markets?, *Journal of Financial Economics* 83, 267-396.

Hughes, John S., Jing Liu, and Jun Liu, 2007, Information asymmetry, diversification, and the cost of capital, *The Accounting Review* 82, 705-729.

Jeng, Leslie A., Andrew Metrick, and Richard Zeckhauser, 2003, Estimating the Returns to Insider Trading: A Performance-Evaluation Perspective, *The Review of Economics and Statistics* 85, 453-471.

Jiang, Xiaoquan, and Mir A. Zaman, 2010, Aggregate insider trading: Contrarian beliefs or superior information?, *Journal of Banking & Finance* 34, 1225-1236.

Ke, Bin, Steven Huddart, and Kathy Petroni, 2003, What insiders know about future earnings and how they use it: Evidence from insider trades, *Journal of Accounting and Economics* 35, 315-346

Lakonishok, Josef, and Immoo Lee, 2001, Are insider trades informative?, *Review of Financial Studies* 14, 79-111.

Pae, Suil, 2014, Demand-enhancing investment, information sharing, and competition, Working paper.

Peress, Joel, 2010, Product market competition, insider trading and stock market efficiency, *Journal of Finance* 65, 1-43.

Piotroski, Joseph D., and Darren T. Roulstone, 2004, The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices, *The Accounting Review* 79, 1119-1151.

Piotroski, Joseph D., and Darren T. Roulstone, 2005, Do insider trades reflect both contrarian beliefs and superior knowledge about future cash flow realizations? *Journal of Accounting and Economics* 39, 55-81.

Pirinsky, Christo, and Qinghai Wang, 2006, Does corporate headquarters location matter for stock returns? Journal of Finance 61, 1991-2015.

Raith, Michael, 1996, A general model of information sharing in oligopoly, *Journal of Economic Theory* 71, 260-288.

Seyhun, Hasan Nejat, 1986, Insiders' profits, costs of trading, and market efficiency, *Journal of Financial Economics* 16, 189-212.

Seyhun, Hasan Nejat, 1988, The information content of aggregate insider trading, *Journal of Business*, 1-24.

Seyhun, Hasan Nejat, 1992, Why does aggregate insider trading predict future stock returns, *The Quarterly Journal of Economics* 107, 1303-1331.

Seyhun, Hasan Nejat, 1998, Investment intelligence from insider trading. MIT press

Tookes, Heather E., 2008, Information, trading, and product market interactions: Cross- sectional implications of informed trading, *Journal of Finance* 63, 379-413.

Vives, Xavier, 1990, Trade association disclosure rules, incentives to share information and welfare, *RAND Journal of Economics* 21, 409-430.

Appendix: Variable Definitions

npr	Net purchase ratio, calculated as the number of purchases minus the number of sales divided by the number of total transactions for each firm during the month.
β_i	Industry-year beta from running equation (1) $r_{i,t} = \beta_i r_{m,t} + \varepsilon_{i,t}$ for each year in our sample period using daily returns where for industry *i* and **day** *t*, $r_{i,t}$ is the value-weighted industry excess return over the risk-free rate and $r_{m,t}$ is the value-weighted market excess return over the risk-free rate. This equation is part of the return decomposition in Campbell et al. (2001).
β_f	Firm-year beta from running equation (2) $r_{f,t} = \beta_f r_{i,t} + \varepsilon_{f,t}$ for each year in our sample period daily returns where for firm *f* and **day** *t*, $r_{f,t}$ is the firm excess return over risk-free rate and $r_{i,t}$ is the value-weighted industry excess return over risk free-rate. This equation is part of the return decomposition in Campbell et al. (2001).
$r_{f,t}^{fs}$	Firm-specific component defined as $r_{f,t} - \hat{\beta}_f \hat{\beta}_i r_{m,t} - \hat{\beta}_f \hat{\varepsilon}_{i,t}$ based on the beta parameters obtained from equations (1) and (2) defined above and from equations (3) $\hat{\varepsilon}_{i,t} = r_{i,t} - \hat{\beta}_{i,y} r_{m,t}$ and (4) $\hat{\varepsilon}_{f,t} = r_{f,t} - \hat{\beta}_{f,y} r_{i,t}$ where firm *f* and/or industry *i* and **month** *t*, $r_{f,t}$ is the firm excess return, $r_{i,t}$ is the value-weighted industry excess return, and $r_{m,t}$ is the value-weighted market excess return.
$r_{f,t+1,t+6}^{fs}$	Firm-specific component of the cumulative excess return for firm *f* from *t*+1 to *t*+6
$r_{f,t-23,t}^{fs}$	Firm-specific component of the cumulative raw return for firm *f* from *t*-23 to *t*
$r_{f,t}^{is}$	Industry-specific component of firm returns defined as $\hat{\beta}_f \hat{\varepsilon}_i$ based on the beta parameters obtained from equations (1) and (2) defined above and from equations (3) $r_{i,t} = \beta_i r_{m,t} + \varepsilon_{i,t}$ and (4) $r_{f,t} = \beta_f r_{i,t} + \varepsilon_{f,t}$ where firm *f* and/or industry *i* and **month** *t*, $r_{f,t}$ is the firm excess return, $r_{i,t}$ is the value-weighted industry excess return, and $r_{m,t}$ is the value-weighted market excess return.
$r_{f,t+1,t+6}^{is}$	Industry-specific component of the cumulative excess return for firm *f* from *t*+1 to *t*+6
$r_{f,t-23,t}^{is}$	Industry-specific component of the cumulative raw return for firm *f* from *t*-23 to *t*
$r_{f,t}^{ew}$	Economy-wide component defined as $\hat{\beta}_f \hat{\beta}_i r_{m,t}$ based on the beta parameters obtained from equations (1) and (2) defined above and from equations (3) $r_{i,t} = \beta_i r_{m,t} + \varepsilon_{i,t}$ and (4) $r_{f,t} = \beta_f r_{i,t} + \varepsilon_{f,t}$ where firm *f* and/or industry *i* and **month** *t*, $r_{f,t}$ is the firm excess return, $r_{i,t}$ is the value-weighted industry excess return, and $r_{m,t}$ is the value-weighted market excess return.
$r_{f,t+1,t+6}^{ew}$	Economy-wide component of the cumulative excess return for firm *f* from *t*+1 to *t*+6
$r_{f,t-23,t}^{ew}$	Economy-wide component of the cumulative raw return for firm *f* from *t*-23 to *t*
MSA	We use COMPUSTAT to obtain the state and county of the firm's headquarters. The firm's location (county and state) is matched to an MSA based on the 2009 delineations by U.S Census Bureau. MSA consists of a core area that contains a substantial population nucleus, together with adjacent communities that have a high degree of social and economic integration with that core. MSAs include one or more entire counties and some MSAs contain counties from several states
LI	Industry-adjusted Lerner Index is defined as operating profits (before depreciation, interest, special items, and taxes) over sales. Operating profits are obtained by subtracting from sales the cost of goods sold and general and administrative expenses. $$Lerner\ Index = \frac{COMPUSTAT\ \#12 - COMPUSTAT\#41 - COMPUSTAT\ \#189}{COMPUSTAT\ \#12}$$

	If data are missing, we use operating income (COMPUSTAT#178). The index is constructed as the difference between the firm's Lerner Index and the Lerner Index of its industry. The industry Lerner Index is the value-weighted average Lerner Index across firms in the industry, where the weights are based on market share (sales over total industry sales).
Segments	Single or multiple business segments for the firm
Price Synchronicity	Price Synchronicity is the logarithmic transformation of R^2 defined as $\log(R^2/(1-R^2))$. R^2 is the coefficient of determination from the firm-year estimation of the model $r_{f,t} = \alpha + \beta_1 r_{m,t-1} + \beta_2 r_{m,t} + \beta_3 r_{i,t-1} + \beta_4 r_{i,t} + \varepsilon_{f,t}$ where $r_{f,t}$ is firm *f*'s return in week *t*, $r_{m,t}$ is the value-weighted market return in week *t*, and $r_{i,t}$ is the value-weighted industry return excluding the firm in week *t*. We estimated this regression for each firm-year with a minimum of 20 weekly observations; where a weekly return is defined as the compounded return over a minimum of four trading days during the week.

Table I
Descriptive Statistics

This table presents the descriptive statistics for our sample. Panel A presents the descriptive statistics for our entire sample that are not specific to the industry classification employed. Our entire sample consists of 1,580,143 firm-month observations from 15,858 unique firms, including all the firms in the intersection of CRSP and COMPUSTAT for 1987-2012. Panel B presents industry-specific descriptive statistics under the 2-digit Standard Industry Classification (SIC-2) code. This sample contains 1,527,407 firm-months and 15,248 unique firms. % of trading firms is the average percentage of firms in our sample that have at least one insider trading (purchase or sale) during a calendar year. # of trades is the average number of trades per firm of our sample; defined as the average of the number of total insider transactions (purchase or sale) for each firm divided by number of active years in the sample. Total $(m) is the average of the aggregate annual insider trading (purchase or sale) in millions of dollars of all companies. % of Mkt Cap is Total $(m) (purchase or sale) as a percentage of the firm's market capitalization at the beginning of the year. Number of segments is the number of business segments for the firm. npr is insiders' net purchase ratio, calculated each month as the number of purchases minus the number of sales divided by the sum of the two numbers for each firm. $r^{fs}_{f,t+1,t+6}$, $r^{is}_{f,t+1,t+6}$, and $r^{ew}_{f,t+1,t+6}$ represent the firm-specific, industry-specific, and economy-wide components of the cumulative excess return for firm *f* from *t*+1 to *t*+6, respectively; $r^{fs}_{f,t-23,t}$, $r^{is}_{f,t-23,t}$, and $r^{ew}_{f,t-23,t}$ represent the firm-specific, industry-specific, and economy-wide component of the cumulative raw return for firm *f* from *t*-23 to *t*, respectively. The return decomposition is based on Campbell et al. (2001). β_i is the industry beta from running regression (1) in the research design section; β_f is the firm beta from running regression (2). The Lerner Index represents product market power and is defined as operating profits divided by sales. Industry-adjusted Lerner Index is defined as the difference between the Lerner Index of the firm and the market-share-weighted-average Lerner Index of its industry. Price synchronicity is calculated as $\log(R^2/(1-R^2))$ where R^2 is the explanatory power of the regression $r_{f,t} = \alpha + \beta_1 r_{m,t-1} + \beta_2 r_{m,t} + \beta_3 r_{i,t-1} + \beta_4 r_{i,t} + \varepsilon_{f,t}$ run for each firm each year with weekly returns.

Panel A: Entire Sample

	Mean	STD	P25	P50	P75
% of trading firms: Purchases	51%	7%	47%	50%	55%
% of trading firms: Sales	57%	10%	51%	58%	67%
# of trades: Purchases	0.56	2.09	0.02	0.14	0.49
# of trades: Sales	1.55	9.57	0.00	0.20	0.83
Total $(m): Purchases	2,772	1,874	1,450	2,253	3,651
Total $(m): Sales	37,569	25,826	11,529	38,229	58,236
%Mkt Cap: Purchases	0.38%	5.81%	0.00%	0.00%	0.06%
%Mkt Cap: Sales	1.02%	5.82%	0.00%	0.03%	0.43%
Number of segments	1.86	1.39	1.00	1.00	3.00
Npr	-0.06	0.49	0.00	0.00	0.00
Non-zero *npr*	-0.24	0.95	-1.00	-1.00	1.00
npr>=0	0.11	0.31	0.00	0.00	0.00
npr<=0	-0.17	0.37	0.00	0.00	0.00

Panel B: SIC-2 Sample

	Mean	STD	P25	P50	P75
$r_{f,t+1,t+6}^{fs}$	0.89%	32.43%	-15.85%	0.76%	17.27%
$r_{f,t+1,t+6}^{is}$	-0.18%	6.33%	-2.57%	-0.01%	2.38%
$r_{f,t+1,t+6}^{ew}$	1.76%	8.73%	-1.01%	1.07%	4.84%
$r_{f,t-23,t}^{fs}$	7.83%	60.27%	-24.58%	6.96%	40.15%
$r_{f,t-23,t}^{is}$	-0.50%	12.51%	-5.54%	-0.13%	4.70%
$r_{f,t-23,t}^{ew}$	6.88%	17.65%	-0.28%	5.19%	14.40%
β_i	1.02	0.29	0.84	1.00	1.21
β_f	0.58	0.49	0.20	0.51	0.93
Industry Adjusted Lerner Index	-0.43	2.11	-0.14	-0.04	0.02
Price Synchronicity	-1.67	1.15	-2.43	-1.70	-0.91

Table II
Insider trading and Future Firm-Specific, Industry-Specific, and Economy-Wide Return Components

This table presents coefficient estimates for the following panel regression: $npr_{f,t} = \alpha + \beta_1 r^{fs}_{f,t+1,t+6} + \beta_2 r^{is}_{f,t+1,t+6} + \beta_3 r^{ew}_{f,t+1,t+6} + \beta_4 r^{fs}_{f,t-23,t} + \beta_5 r^{is}_{f,t-23,t} + \beta_6 r^{ew}_{f,t-23,t} + \varepsilon_{f,t}$. $npr_{f,t}$ is the insiders' net purchase ratio for firm *f* during month *t*, calculated as the difference between the number of purchase transactions and the number of sale transactions divided by the sum of the two numbers; $r^{fs}_{f,t+1,t+6}$, $r^{is}_{f,t+1,t+6}$, and $r^{ew}_{f,t+1,t+6}$ represent the firm-specific, industry-specific, and economy-wide components of the cumulative excess return for firm *f* from *t*+1 to *t*+6, respectively; $r^{fs}_{f,t-23,t}$, $r^{is}_{f,t-23,t}$, and $r^{ew}_{f,t-23,t}$ represent the firm-specific, industry-specific, and economy-wide components of the cumulative raw return for firm *f* from *t*-23 to *t*, respectively. The return decomposition is based on Campbell et al. (2001). Industries are defined according to the 2-digit Standard Industry Classification (SIC-2), Fama-French 48 industry classification (FF48), North American Industry Classification System 3-digit classification (NAICS-3), FIC 100 and TNIC-3. FIC 100 and TNIC-3 are based on text analyses of the product descriptions by companies (Hoberg and Phillips, 2010). Firm and year fixed effects are included in the regressions to control for firm characteristics and time trends that may drive non-private information based insider trading. Please refer to the research design section for further details. Numbers in parentheses are t-statistics calculated by clustering the standard errors by firm and month. ***, **, and *, denote significance levels at the 1%, 5%, and 10%, respectively.

	SIC-2		FF48		NAICS-3		FIC 100		TNIC-3	
$r^{fs}_{f,t+1,t+6}$	0.063	***	0.062	***	0.063	***	0.060	***	0.066	***
	(20.90)		(20.42)		(20.79)		(12.61)		(12.90)	
$r^{is}_{f,t+1,t+6}$	0.003		0.015		0.018		-0.014		-0.043	*
	(0.14)		(0.79)		(1.02)		(0.69)		(1.93)	
$r^{ew}_{f,t+1,t+6}$	0.189	***	0.195	***	0.192	***	0.248	***	0.246	***
	(6.97)		(7.08)		(6.99)		(5.41)		(5.18)	
$r^{fs}_{f,t-23,t}$	-0.101	***	-0.102	***	-0.101	***	-0.115	***	-0.109	***
	(41.96)		(41.89)		(41.29)		(28.15)		(26.17)	
$r^{is}_{f,t-23,t}$	-0.202	***	-0.194	***	-0.193	***	-0.224	***	-0.216	***
	(18.07)		(16.43)		(18.02)		(13.07)		(12.82)	
$r^{ew}_{f,t-23,t}$	-0.174	***	-0.173	***	-0.176	***	-0.196	***	-0.189	***
	(12.77)		(12.42)		(12.69)		(9.44)		(9.19)	
Firm fixed effect	Yes		Yes		Yes		Yes		Yes	
Year fixed effect	Yes		Yes		Yes		Yes		Yes	
R^2	15.8%		15.8%		15.8%		19.9%		20.6%	
N.	1,527,407		1,534,524		1,523,080		604,347		504,252	

Table III
Insider Trading and Future Returns: Purchases vs. Sales

This table presents the coefficient estimates of panel regressions similar to those in Table II with the sample partitioned into insider purchases and insider sales. Panel A (B) presents the coefficient estimates based on the sample where $npr_{f,t}$ is larger (smaller) than or equal to 0. $npr_{f,t}$ is insiders' net purchase ratio for firm *f* during month *t*, calculated as the difference between the number of purchase transactions and the number of sale transactions divided by the sum of the two numbers; $r^{fs}_{f,t+1,t+6}$, $r^{is}_{f,t+1,t+6}$, and $r^{ew}_{f,t+1,t+6}$ represent the firm-specific, industry-specific, and economy-wide components of the cumulative excess returns for firm *f* from *t*+1 to *t*+6, respectively; $r^{fs}_{f,t-23,t}$, $r^{is}_{f,t-23,t}$, and $r^{ew}_{f,t-23,t}$ represent the firm-specific, industry-specific, and economy-wide components of the cumulative raw return for firm *f* from *t*-23 to *t*, respectively. The return decomposition is based on Campbell et al. (2001). Industries are defined according to the 2-digit Standard Industry Classification (SIC-2), Fama-French 48 industry classification (FF48), North American Industry Classification System 3-digit classification (NAICS-3), FIC 100 and TNIC-3. FIC 100 and TNIC-3 are based on text analyses of the product descriptions by companies (Hoberg and Phillips, 2010). Firm and year fixed effects are included in the regressions to control for firm characteristics and time trend that may drive non-private information based insider trading. Please refer to the research design section for further details. Numbers in parentheses are t-statistics calculated by clustering the standard errors by firm and month. ***, **, and *, denote significance levels at the 1%, 5%, and 10%, respectively.

Panel A: Insiders Purchases ($npr_{f,t} \geq 0$)

	SIC-2		FF48		NAICS-3		FIC 100		TNIC-3	
$r^{fs}_{f,t+1,t+6}$	0.031	***	0.031	***	0.032	***	0.027	***	0.028	***
	(17.78)		(17.43)		(18.06)		(10.68)		(10.45)	
$r^{is}_{f,t+1,t+6}$	0.001		-0.004		0.002		-0.027	**	-0.033	***
	(0.11)		(0.37)		(0.20)		(2.54)		(2.80)	
$r^{ew}_{f,t+1,t+6}$	0.082	***	0.086	***	0.086	***	0.090	**	0.081	*
	(3.66)		(3.73)		(3.68)		(2.23)		(1.96)	
$r^{fs}_{f,t-23,t}$	-0.024	***	-0.024	***	-0.024	***	-0.030	***	-0.029	***
	(19.88)		(19.71)		(19.72)		(15.20)		(14.44)	
$r^{is}_{f,t-23,t}$	-0.060	***	-0.061	***	-0.062	***	-0.073	***	-0.064	***
	(9.76)		(9.21)		(10.13)		(8.86)		(8.13)	
$r^{ew}_{f,t-23,t}$	-0.044	***	-0.045	***	-0.045	***	-0.065	***	-0.066	***
	(4.67)		(4.72)		(4.82)		(3.88)		(4.21)	
Firm fixed effect	Yes		Yes		Yes		Yes		Yes	
Year fixed effect	Yes		Yes		Yes		Yes		Yes	
R^2	10.3%		10.3%		10.3%		12.5%		13.1%	
N.	1,285,144		1,290,655		1,281,153		489,624		405,524	

Panel B: Insiders Sales ($npr_{f,t} \leq 0$)

	SIC-2		FF48		NAICS-3		FIC 100		TNIC-3	
$r^{fs}_{f,t+1,t+6}$	0.031	***	0.030	***	0.031	***	0.033	***	0.038	***
	(14.05)		(13.63)		(13.74)		(8.86)		(9.49)	
$r^{is}_{f,t+1,t+6}$	0.003		0.020		0.017		0.015		-0.009	
	(0.25)		(1.48)		(1.31)		(0.95)		(0.53)	
$r^{ew}_{f,t+1,t+6}$	0.112	***	0.114	***	0.112	***	0.161	***	0.168	***
	(4.19)		(4.29)		(4.19)		(3.71)		(3.84)	
$r^{fs}_{f,t-23,t}$	-0.076	***	-0.076	***	-0.075	***	-0.084	***	-0.080	***
	(40.01)		(39.80)		(39.15)		(25.40)		(23.66)	
$r^{is}_{f,t-23,t}$	-0.140	***	-0.130	***	-0.129	***	-0.152	***	-0.150	***
	(17.02)		(15.48)		(16.95)		(12.20)		(12.17)	
$r^{ew}_{f,t-23,t}$	-0.125	***	-0.124	***	-0.126	***	-0.129	***	-0.122	***
	(8.93)		(8.69)		(8.77)		(6.92)		(6.60)	
Firm fixed effect	Yes		Yes		Yes		Yes		Yes	
Year fixed effect	Yes		Yes		Yes		Yes		Yes	
R^2	18.6%		18.6%		18.5%		20.5%		20.8%	
N.	1,383,679		1,390,362		1,379,879		543,091		452,283	

Table IV
Insider Trading and Future Returns: Firms with Common Geographic Location of Their Headquarters

This table presents the coefficient estimates of panel regressions similar to those in Table II, classifying firms that have the same industry classification, such as SIC-2 or NAICS-3, *and* whose headquarters are located in the same metropolitan statistical areas (MSA) as a unique industry/MSA group. Panel A presents the coefficient estimates for the entire sample; Panel B (C) presents the coefficients estimates based on the sample where $npr_{f,t}$ is larger (smaller) than or equal to 0. $npr_{f,t}$ is insiders' net purchase ratio for firm *f* during month *t*, calculated as the difference between the number of purchase transactions and the number of sale transactions divided by the sum of the two numbers; $r^{fs}_{f,t+1,t+6}$, $r^{is}_{f,t+1,t+6}$, and $r^{ew}_{f,t+1,t+6}$ represent the firm-specific, industry-specific, and economy-wide components of the cumulative excess return for firm *f* from *t*+1 to *t*+6, respectively. Firm-specific, industry-specific, and economy-wide components of firms' past returns are used as control variables. The return decomposition is based on Campbell et al. (2001). Each column represents the industry classification based on MSA and one industry classification from any of the 2-digit Standard Industry Classification (SIC-2), Fama-French 48 industry classification (FF48), North American Industry Classification System 3-digit classification (NAICS-3), FIC 100 and TNIC-3. FIC 100 and TNIC-3 are based on text analyses of the product descriptions by companies (Hoberg and Phillips, 2010). Firm and year fixed effects are included in the regressions to control for firm characteristics and time trend that may drive non-information based insider trading. Please refer to the research design section for further details. Numbers in parentheses are t-statistics calculated by clustering the standard errors by firm and month. ***, **, and *, denote significance levels at the 1%, 5%, and 10%, respectively.

Panel A: Entire Sample

	SIC-2		FF48		NAICS-3		FIC 100		TNIC-3	
$r^{fs}_{f,t+1,t+6}$	0.061	***	0.060	***	0.060	***	0.059	***	0.066	***
	(18.54)		(19.00)		(18.25)		(11.76)		(10.72)	
$r^{is}_{f,t+1,t+6}$	0.031	**	0.044	***	0.054	***	0.035	**	-0.022	
	(2.49)		(3.42)		(4.11)		(1.97)		(0.71)	
$r^{ew}_{f,t+1,t+6}$	0.179	***	0.181	***	0.162	***	0.234	***	0.228	***
	(5.96)		(5.92)		(5.39)		(4.90)		(4.05)	
Past returns	Yes		Yes		Yes		Yes		Yes	
Firm fixed effect	Yes		Yes		Yes		Yes		Yes	
Year fixed effect	Yes		Yes		Yes		Yes		Yes	
R^2	17.3%		17.4%		17.3%		20.1%		22.5%	
N.	719,138		747,313		688,153		269,959		163,051	

Panel B: Insider Purchases ($npr_{f,t} \geq 0$)

	SIC-2		FF48		NAICS-3		FIC 100		TNIC-3	
$r^{fs}_{f,t+1,t+6}$	0.028	***	0.029	***	0.029	***	0.027	***	0.022	***
	(14.52)		(15.42)		(14.95)		(9.33)		(6.94)	
$r^{is}_{f,t+1,t+6}$	0.009		0.005		0.013	*	0.007		-0.024	*
	(1.27)		(0.71)		(1.72)		(0.81)		(1.68)	
$r^{ew}_{f,t+1,t+6}$	0.077	***	0.078	***	0.072	***	0.090	**	0.065	
	(3.35)		(3.29)		(3.13)		(2.55)		(1.46)	
Past returns	Yes		Yes		Yes		Yes		Yes	
Firm fixed effect	Yes		Yes		Yes		Yes		Yes	
Year fixed effect	Yes		Yes		Yes		Yes		Yes	
R^2	10.5%		10.8%		10.8%		11.0%		13.2%	
N.	599,486		622,613		573,965		216,705		127,581	

Panel C: Insider Sales ($npr_{f,t} \leq 0$)

	SIC-2		FF48		NAICS-3		FIC 100		TNIC-3	
$r^{fs}_{f,t+1,t+6}$	0.032	***	0.030	***	0.030	***	0.032	***	0.043	***
	(12.73)		(12.46)		(11.82)		(8.10)		(8.48)	
$r^{is}_{f,t+1,t+6}$	0.024	**	0.040	***	0.042	***	0.030	**	0.003	
	(2.28)		(4.02)		(4.03)		(2.01)		(0.11)	
$r^{ew}_{f,t+1,t+6}$	0.106	***	0.108	***	0.094	***	0.149	***	0.165	***
	(3.69)		(3.81)		(3.29)		(3.51)		(3.09)	
Past returns	Yes		Yes		Yes		Yes		Yes	
Firm fixed effect	Yes		Yes		Yes		Yes		Yes	
Year fixed effect	Yes		Yes		Yes		Yes		Yes	
R^2	20.3%		20.4%		20.2%		21.5%		22.9%	
N.	657,059		682,432		628,064		246,156		147,846	

Table V
Insider Trading and Future Returns: Low, Medium and High Product Market Power

This table presents the coefficient estimates of panel regressions similar to those in Table II, partitioning firms into low, medium, and high product market power based on their industry-adjusted Lerner Index. The Lerner Index represents the product market power of the firm and is defined as operating profits divided by sales. Industry adjusted Lerner index is defined as the difference between the Lerner index of the firm and the market-share-weighted-average Lerner Index of its industry. Panels A and B present the results based on FIC 100 and TNIC-3 text-based industry classification (Hoberg and Philips, 2010), respectively. Within each panel, we present the coefficient estimates for the entire sample and the coefficients estimates based on the subsample where $npr_{f,t}$ is larger (smaller) than or equal to 0. $npr_{f,t}$ is the net purchase ratio for firm *f* during month *t*, calculated as the difference between the number of purchase transactions and the number of sale transactions divided by the sum of the two numbers; $r^{fs}_{f,t+1,t+6}$, $r^{is}_{f,t+1,t+6}$, and $r^{ew}_{f,t+1,t+6}$ represent the firm-specific, industry-specific, and economy-wide components of the cumulative excess return for firm *f* from *t*+1 to *t*+6, respectively. Firm-specific, industry-specific, and economy-wide components of firms' past returns are used as control variables. The return decomposition is based on Campbell et al. (2001). Firm and year fixed effects are included in the regressions to control for firm characteristics and time trend that may drive non-private information based insider trading. Please refer to the research design section for further details. Numbers in parentheses are t-statistics calculated by clustering the standard errors by firm and month. ***, **, and *, denote significance levels at the 1%, 5%, and 10%, respectively.

Panel A: Results based on FIC 100

	Entire Sample						Insider Purchases ($npr_{f,t} \geq 0$)						Insider Sales ($npr_{f,t} \leq 0$)					
	Low		Med		High		Low		Med		High		Low		Med		High	
$r^{fs}_{f,t+1,t+6}$	0.048	***	0.093	***	0.098	***	0.022	***	0.042	***	0.041	***	0.025	***	0.052	***	0.059	***
	(9.95)		(13.83)		(12.91)		(7.08)		(9.04)		(9.35)		(6.50)		(9.93)		(9.45)	
$r^{is}_{f,t+1,t+6}$	0.023		0.046	*	-0.013		-0.011		0.005		-0.031	**	0.038		0.045	**	0.023	
	(0.83)		(1.72)		(0.47)		(0.74)		(0.36)		(2.02)		(1.57)		(1.97)		(1.06)	
$r^{ew}_{f,t+1,t+6}$	0.200	***	0.275	***	0.297	***	0.062		0.107	**	0.117	***	0.139	***	0.177	***	0.191	***
	(4.37)		(5.28)		(5.15)		(1.48)		(2.42)		(2.72)		(3.55)		(3.34)		(3.44)	
Past returns	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Firm fixed effect	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Year fixed effect	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
R^2	20.4%		22.3%		22.5%		14.3%		15.0%		15.0%		22.2%		22.3%		21.6%	
N.	199,117		199,134		199,095		172,349		162,279		148,566		178,828		177,486		180,437	
F Test: Low Group < High Group																		
$r^{fs}_{f,t+1,t+6}$					38.94	***					9.96	***					29.85	***
$r^{is}_{f,t+1,t+6}$					0.33						1.39						0.01	
$r^{ew}_{f,t+1,t+6}$					5.34	**					16.79	***					0.48	

Panel B: Results based on TNIC-3

	Panel A: Entire Sample						Panel B: Insider Purchases						Panel C: Insider Sales					
	Low		Med		High		Low		Med		High		Low		Med		High	
$r^{fs}_{f,t+1,t+6}$	0.052	***	0.099	***	0.109	***	0.025	***	0.041	***	0.040	***	0.027	***	0.061	***	0.071	***
	(10.08)		(13.52)		(13.06)		(7.42)		(8.26)		(7.97)		(6.52)		(10.07)		(10.91)	
$r^{is}_{f,t+1,t+6}$	0.027		0.023		-0.056	**	-0.008		0.007		-0.020		0.038		0.022		-0.033	
	(0.89)		(0.86)		(2.05)		(0.46)		(0.46)		(1.23)		(1.48)		(0.95)		(1.53)	
$r^{ew}_{f,t+1,t+6}$	0.197	***	0.302	***	0.293	***	0.049		0.129	***	0.101	**	0.150	***	0.193	***	0.197	***
	(4.22)		(5.29)		(4.88)		(1.16)		(2.72)		(2.32)		(3.87)		(3.53)		(3.44)	
Past returns	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Firm fixed effect	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Year fixed effect	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
R^2	20.9%		23.3%		22.8%		15.2%		16.3%		14.8%		22.1%		22.9%		21.9%	
N.	165,860		165,896		165,858		143,060		134,049		122,309		148,282		147,155		150,843	
F Test: Low Group < High Group																		
$r^{fs}_{f,t+1,t+6}$					46.58	***					6.19	***					49.60	***
$r^{is}_{f,t+1,t+6}$					0.33						1.39						2.85	*
$r^{ew}_{f,t+1,t+6}$					3.37	*					9.87	***					0.25	

Table VI

Insider Trading and Future Returns: Low, Medium and High Price Synchronicity

This table presents the coefficient estimates of panel regressions similar to those in Table II, partitioning firms into low, medium, and high price synchronicity. Price synchronicity is calculated as $\log(R^2/(1-R^2))$ where R^2 is the explanatory power of the regression $r_{f,t} = \alpha + \beta_1 r_{m,t-1} + \beta_2 r_{m,t} + \beta_3 r_{i,t-1} + \beta_4 r_{i,t} + \varepsilon_{f,t}$ run for each firm each year with weekly returns. Industry is defined by the 2-digit SIC code. Panel A presents the coefficient estimates for the entire sample; Panel B (C) presents the coefficients estimates based on the sample where $npr_{f,t}$ is larger (smaller) than or equal to 0. $npr_{f,t}$ is the net purchase ratio for firm f during month t, calculate as the difference between the number of purchase transactions and the number of sale transactions divided by the sum of the two numbers; $r^{fs}_{f,t+1,t+6}$, $r^{is}_{f,t+1,t+6}$, and $r^{ew}_{f,t+1,t+6}$ represent the firm-specific, industry-specific, and economy-wide components of the cumulative excess return for firm f from t+1 to t+6, respectively. Firm-specific, industry-specific, and economy-wide components of firms' past returns are used as control variables. The return decomposition is based on Campbell et al. (2001). Firm and year fixed effects are included in the regressions to control for firm characteristics and time trend that may drive non-information based insider trading. Please refer to the research design section for further details. Numbers in parentheses are t-statistics calculated by clustering the standard errors by firm and month. ***, **, and *, denote significance levels at the 1%, 5%, and 10%, respectively.

	Panel A: Entire Sample						Panel B: Insider Purchases ($npr_{f,t} \geq 0$)						Panel C: Insider Sales ($npr_{f,t} \leq 0$)					
	Low		Med		High		Low		Med		High		Low		Med		High	
$r^{fs}_{f,t+1,t+6}$	0.053	***	0.065	***	0.083	***	0.030	***	0.032	***	0.038	***	0.022	***	0.032	***	0.045	***
	(16.96)		(17.54)		(16.03)		(13.75)		(14.01)		(12.32)		(9.88)		(11.25)		(11.46)	
$r^{is}_{f,t+1,t+6}$	0.029		0.002		-0.007		0.029	*	0.013		-0.001		-0.001		-0.009		0.000	
	(1.24)		(0.08)		(0.28)		(1.72)		(0.91)		(0.09)		(0.07)		(0.53)		0.00	
$r^{ew}_{f,t+1,t+6}$	0.093	***	0.191	***	0.243	***	0.049		0.097	***	0.081	***	0.044	*	0.105	***	0.167	***
	(3.26)		(6.76)		(6.58)		(1.59)		(3.20)		(3.30)		(1.72)		(3.42)		(5.01)	
Past returns	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Firm fixed effect	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Year fixed effect	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
R^2	15.7%		19.1%		17.3%		13.6%		13.4%		11.8%		18.8%		21.5%		18.4%	
N.	506,986		506,993		506,971		457,867		430,418		390,724		455,667		459,559		462,709	
F Test: Low < High Price Synchronicity																		
$r^{fs}_{f,t+1,t+6}$					35.77	***					3.21	*					42.07	***
$r^{is}_{f,t+1,t+6}$					0.85						4.25	**					0.72	
$r^{ew}_{f,t+1,t+6}$					5.18	**					0.51						6.74	***

Table VII

Insider Trading and Future Returns: Single- vs. Multi-Segment Firms

This table presents the coefficient estimates of panel regressions similar to those in Table II, partitioning firms into single- and multi-segment firms. Number of segments is the number of business segments for the firm. Industry is defined by the 2-digit SIC code. Panel A presents the coefficient estimates for the entire sample; Panel B (C) presents the coefficients estimates based on the sample where $npr_{f,t}$ is larger (smaller) than or equal to 0. $npr_{f,t}$ is the net purchase ratio for firm *f* during month *t*, calculate as the difference between the number of purchase transactions and the number of sale transactions divided by the sum of the two numbers; $r^{fs}_{f,t+1,t+6}$, $r^{is}_{f,t+1,t+6}$, and $r^{ew}_{f,t+1,t+6}$ represent the firm-specific, industry-specific, and economy-wide components of the cumulative excess return for firm *f* from *t*+1 to *t*+6, respectively. Firm-specific, industry-specific, and economy-wide components of firms' past returns are used as control variables. The return decomposition is based on Campbell et al. (2001). Firm and year fixed effects are included in the regressions to control for firm characteristics and time trend that may drive non-private information based insider trading. Please refer to the research design section for further details. Numbers in parentheses are t-statistics calculated by clustering the standard errors by firm and month. ***, **, and *, denote significance levels at the 1%, 5%, and 10%, respectively.

	Panel A: Entire Sample				Panel B: Insider Purchases ($npr_{f,t} \geq 0$)				Panel C: Insider Sales ($npr_{f,t} \leq 0$)			
	Single		Multi		Single		Multi		Single		Multi	
$r^{fs}_{f,t+1,t+6}$	0.063	***	0.070	***	0.030	***	0.037	***	0.031	***	0.034	***
	(20.49)		(15.63)		(16.43)		(13.60)		(13.78)		(9.91)	
$r^{is}_{f,t+1,t+6}$	0.015		-0.011		-0.001		0.008		0.018		-0.017	
	(0.71)		(0.49)		(0.06)		(0.64)		(1.21)		(0.97)	
$r^{ew}_{f,t+1,t+6}$	0.163	***	0.246	***	0.078	***	0.088	***	0.090	***	0.163	***
	(6.08)		(7.54)		(3.50)		(3.45)		(3.48)		(5.06)	
Past returns	Yes		Yes		Yes		Yes		Yes		Yes	
Firm fixed effect	Yes		Yes		Yes		Yes		Yes		Yes	
Year fixed effect	Yes		Yes		Yes		Yes		Yes		Yes	
R^2	16.9%		16.5%		11.8%		9.6%		20.0%		18.6%	
N.	1,062,609		464,798		902,302		382,842		960,026		423,653	
F Test: Single < Multi-Segment												
$r^{fs}_{f,t+1,t+6}$			0.08				2.74	*			0.09	
$r^{is}_{f,t+1,t+6}$			1.20				0.05				2.70	
$r^{ew}_{f,t+1,t+6}$			4.69	**			1.59				3.29	*