Characteristics of Cash Flow News and Informational Environment*

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ABSTRACT

By examining the profitability of insider trading, this paper investigates whether the characteristics of cash flow news of a firm affect its informational environment. When a firm's cash flow news is very sensitive to industry-wide cash flow news, insiders are not likely to have many informational advantages. For the overall sample, the empirical findings align with this hypothesis, indicating that the characteristics of a firm's cash flow news could influence its informational environment. However, this primarily applies to companies that often encounter greater information asymmetry, such as smaller firms or firms with less liquid stocks.

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I. Introduction

A firm's information environment plays a central role in asset pricing and managerial decisions, making it essential to understand the factors that shape it. In this paper, we examine whether the characteristics of cash flow news affect a firm's informational environment by studying insiders' trading profitability. Specifically, we investigate whether insiders earn significantly less abnormal profits from their insider transactions when their firms' cash flow news is highly sensitive to industry-wide cash flow news, thereby making it easier to infer. While numerous studies have examined the importance of cash flow news compared to discount rate news, little is known about how the nature of cash flow news itself affects the flow and processing of the information. To the best of our knowledge, this paper is the first to present evidence on how the characteristics of a firm's cash flow news influence its informational environment.

According to the discounted cash flow approach, stock prices should reflect both cash flow news and discount rate news. It seems natural to believe that cash flow news is more firm-specific, while discount rate news is more influenced by market-wide factors. Therefore, insiders are likely to possess more private information on cash flow news than on discount rate news. However, previous studies offer conflicting evidence regarding this conjecture.

In an earlier study, Vuolteenaho (2002) shows that cash flow news tends to be more firm-specific than discount rate news, which is generally systematic and highly correlated across firms. However, Da and Warachka (2009) provides evidence suggesting that a significant portion of cash flow news might be systematic. In addition, Savor and Wilson (2016) and Ben-Rephael, Carlin, Da, and Israelsen (2021) provide evidence supporting the idea that investors can learn about the prospects of non-announcing peer firms' earnings from the announcements of announcing firms' earnings. These studies indicate that cash flow news includes systematic components and, therefore, may not be purely firm-specific. In a recent paper, Lochstoer and Tetlock (2020) show that systematic cash flow news drives the returns of anomaly portfolios while anomaly discount rate shocks are uncorrelated with market discount rate shocks.

Moreover, there are studies documenting that cash flow news better explains returns over longer horizons and has permanent effects on stock returns, while discount rate news is more responsible for short-term price movements. For example, Chen, Da, and Zhao (2013) show that, at the individual firm level, cash flow news explains 63% of the variance of stock returns over the two-year horizon while it explains 48% over the one-year horizon. Similarly, Campbell and Vuolteenaho (2004) emphasize the permanent effects of cash flow news and the temporary nature of discount rate news, and call the sensitivity of stock returns to the

market's cash flow news bad beta requiring higher compensation and the sensitivity to the market's discount rate news good beta requiring lower compensation.

In this paper, we investigate whether the characteristics of cash flow news affect the informational environment of a firm by examining the profitability of insider trading across firms with different sensitivities of firm cash flow news to industry-wide cash flow news. Insiders are likely to take advantage of private information regarding longer-term values than shorter-term values of their firms because of the short-swing rule (Section 16(b) of the Securities and Exchange Act of 1934), according to which insiders are required to return any profits made from a round-trip transaction of less than six months. Due to this regulation, insiders can benefit from their insider transactions only when their investment horizons are longer than six months, implying that they can exploit only those trading opportunities that affect stock returns over horizons longer than six months. Therefore, insiders are likely to exploit their private information on cash flow news more than their informational advantages on discount rate news, which tends to affect shorter-term returns.

Regarding the ability of insiders to predict future cash flows of their firms, Piotroski and Roulstone (2005) present evidence that insiders possess private information on future cash flow news. However, as shown by Da and Warachka (2009), if a large part of the cash flow news of a firm is systematic, it is not so obvious whether even insiders of firms with cash flow news that is very sensitive to industry-wide cash flow news are able to make as much abnormal profits as those of firms with less sensitive cash flow news. When cash flow news of a firm is very sensitive to industry-wide cash flow news, insiders of such firms are less likely to have informational advantages regarding their cash flow news unless they possess private information on industry-wide cash flow news. This paper investigates this question using insider transactions made by top managers of US-listed firms and estimating systematic cash flow news based on a method similar to those used in Da and Warachka (2009) and Da, Liu, and Schaumburgh (2014).

Even though trading on material non-public information is illegal in the US and many other countries, previous studies (e.g., Seyhun (1986)) document that insiders earn abnormal profits from their self-reported personal transactions of their firms' shares.[1] Moreover, Lakonishok and Lee (2001) show that even outsiders who base their investment decisions on reported insider transactions can outperform benchmarks over the 12-month horizon, especially when they focus on purchase transactions of small firms.[2] Considering that purchase

[1] In a recent paper, Anginer, Hoberg, and Seyhun (2018) provide evidence that insiders exploit anomalies arising from mispricing, and disclosures of their transactions expedite the disappearance of mispricing, improving price efficiency.

[2] Bettis, Coles, and Lemmon (2000) show that many firms adopt voluntary insider trading restrictions, and as a result, the profitability of insider transactions has diminished. However, there are some studies showing

transactions typically involve lower litigation risk, as shown in Rogers (2008), the evidence is consistent with the possibility that insiders of firms with higher degrees of information asymmetry exploit their informational advantages by participating in transactions involving lower legal risk. Although there is a great deal of anecdotal evidence on the types of information insiders take advantage of, [3] academic studies have not paid close attention to whether the characteristics of cash flow news of a firm affect its insiders' personal trading decisions.

Using insider transactions made by top managers of the firms listed in major US exchanges over the period between January 1988 and June 2020, we first document whether insiders earn abnormal profits using various ways to measure abnormal profits. Consistent with previous studies' results, we find that insiders tend to buy shares after poor performance of their stocks and earn abnormal profits from their purchase transactions. Moreover, we find that the results are driven primarily by insider transactions of smaller firms.

For example, the equally-weighted average size, book-to-market equity ratio (BM), and momentum-adjusted one-year buy-and-hold abnormal returns (BHAR) of buyers is -12.30% prior to the time when firms are classified as buyers and the equally-weighted average six-month BHAR after the classification is 0.51%, both of which are significant at the one percent significance level. However, once value-weighted averages are examined, the results become insignificant after classification, although prior abnormal return results hold.

Similarly to the procedures in Da and Warachka (2009) and Da et al. (2014), in each month during my sample period, we estimate cash flow news and then measure how sensitive the cash flow news of a firm is to industry-wide cash flow news by running regressions of individual cash flow news on industry-wide cash flow news. The slope coefficients of industry-wide cash flow news are used as a measure of systematic cash flow news (SCFN) for each company.

The empirical findings based on two methods of estimating abnormal returns provide minimal support for the hypothesis that the characteristics of CFN influence the abnormal

that insiders continue to earn abnormal profits, especially from their purchase transactions, despite voluntary corporate restrictions on insider trading (e.g., Jagolinzer, Larcker, and Taylor (2011) and Lee, Lemmon, Li, and Sequeira (2014)). Furthermore, studies show that money managers track insider transactions even in more recent periods (Chen, Cohen, Gurun, Lou, and Malloy (2020)), and the market responds instantly to the release of insider transaction information, especially information about purchases (Rogers, Skinner, and Zechman (2017)).

[3]The US Securities and Exchange Commission (SEC) provides a list of insider trading enforcement actions taken by the SEC on its website (`https://www.sec.gov/spotlight/insidertrading/cases.shtml`). The Insider Trading and Securities Fraud Enforcement Act of 1988 (ITSFEA), the Stock Enforcement Remedies and Penny Stock Reform Act of 1990 (SERPSRA), and the Private Securities Litigation Reform Act of 1995 (PSLRA) are important regulations regarding insider trading and Bhattacharya and Daouk (2002) document that out of 103 countries, 87 countries have insider trading laws, but enforcement has taken place in only 38 countries.

profits earned by insiders from their personal transactions. However, regression analyses that address potential endogeneity concerns reveal robust evidence. Insiders in firms with more systematic cash flow news gain significantly lower returns after adjusting for various factors affecting stock return. Moreover, the results remain similar even if we use only non-routine insider transactions as defined in Cohen, Malloy, and Pomorski (2012), which are known to be more informative.

Finally, in subsample analyses, we find that the results are restricted to those firms that are likely to have more information asymmetry, smaller firms, and firms with low stock liquidity. This last result indicates that the characteristics of cash flow news could play an important role in determining the informational environment of firms that are known to be more exposed to information asymmetry. This might be possible because insiders' informational advantages are likely to be limited when their cash flow news depends a lot on industry-wide cash flow news, even though insiders of the firms with more asymmetric information, in general, possess a large amount of private information.

In summary, this paper presents new evidence regarding how the characteristics of cash flow news influence the informativeness of insider trading, providing insights into their association with a firm's informational environment. Some empirical results are consistent with the characteristics of cash flow news being associated with profits earned by insiders from personal transactions, possibly due to their influence on the informational environment of firms.

The remainder of the paper is organized as follows. Section II describes the methodology and data, as well as providing summary statistics. Section III presents the main empirical results, and Section IV provides the results of the robustness checks. Section V concludes.

II. Methodology, Data, and Summary Statistics

A. Methodology

To measure insider trading activities of a firm, we use a measure used in Lakonishok and Lee (2001), net purchase ratio (NPR). At the end of each month with insider transactions, the NPR is calculated based on open-market/private buy and sell transactions made by the top managers of each sample firm during the past six months, including the month of NPR calculations.

According to Section 16(a) of the Securities and Exchange Act of 1934, top managers and large shareholders with more than 10% of ownership are required to report their transactions to the US Securities and Exchange Commission (SEC). In this study, to focus on those

insiders who are likely to possess private information on cash flow news, we restrict the sample to include only those transactions made by C-suite managers, chairmen of the board, directors, officers, presidents, and vice presidents.

NPR is defined as the ratio of the number of buy transactions minus the number of sell transactions to the total number of buy and sell transactions during the six-month period ending at the end of each month. To exclude cases involving transactions of limited significance, NPRs involving less than three insider transactions made by top managers during the past six months are excluded.[4] A six-month period is used since it is the minimum holding period required to avoid any penalties from the short-swing rule. As explained earlier, according to the short-swing rule (Section 16(b) of the Securities and Exchange Act of 1934), insiders are required to return any profits made from a round-trip transaction of less than six months. To ensure that NPR is based on multiple transactions, NPR is estimated only when the number of all transactions during a period of six months is greater than or equal to three. After measuring NPR, firms with available NPR estimates are divided into four NPR groups using absolute cutoff points: -0.95, 0.00, and 0.95.[5]

To verify the robustness of the results, the analyses are repeated after excluding those that are considered routine transactions based on the method of Cohen et al. (2012) in Section IV.[6] Cohen et al. (2012) show that insiders do not earn abnormal profits from their seemingly routine transactions.

Turning to the measurement of cash flow news (CFN), we estimate it using a method similar to those in Da and Warachka (2009) and Da et al. (2014). One of the advantages of using this method, compared to other alternatives such as the implied costs of capital-based approach (e.g., Chen et al. (2013)) is that CFN can be estimated in monthly intervals during the sample period and, therefore, it is more convenient to measure systematic cash flow news using a regression approach.[7] More details are described in Appendix B but we briefly explain the main ideas behind the method here.

In each month, a firm's cash flow news component of unexpected log returns is estimated

[4]Lakonishok and Lee (2001) show that an NPR measure based on the number of transactions is more informative than an NPR measure based on the dollar volume of transactions.

[5]This is to make sure that the highest NPR quartile is composed of the firms with mostly purchase transactions. Since there are more sale transactions than purchase transactions, the highest NPR quartile may not be made up of firms with mostly buy transactions if quartiles are formed based on the same number of firms. The use of several alternative cutoff points does not change the qualitative results. As reported in Table I, out of the 145,105 total firm-month sample observations, there are 77,031 observations in the sell group (the lowest NPR quartile) and 14,314 observations in the buy group (the highest NPRQ)

[6]As in Cohen et al. (2012), after identifying insiders who trade in the same calendar month for three consecutive years in the past, all their following transactions are treated as routine transactions and excluded from the analyses in Section IV.

[7]Chen et al. (2013) measure cash flow news in quarterly intervals since they use actual quarterly dividend payments to estimate payout ratios.

by calculating the change in the expected cash flow component over a month. Earnings forecasts made by financial analysts are used to estimate expected cash flow components by using the unexpected real stock return decomposition of Campbell (1991) and the clean-surplus accounting identity as used in Vuolteenaho (2002).

Campbell (1991) shows that a cash flow news component of the unexpected log stock return can be represented as $(E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j \Delta d_{t+j+1}$, where ρ is a log-linearization factor, and Δd_{t+j+1} is the change in the expected log dividend at time $t+j+1$. Here, the cash flow news component is based on future log dividends that are different from future log earnings. Vuolteenaho (2002) uses the clean surplus accounting identity (that is, $B_{t+1} = B_t + X_{t+1} - D_{t+1}$, where B, X, and D represent the book value of equity, earnings, and dividend, respectively), and shows that Δd_{t+j+1} in the equation of the cash flow component can be replaced with log returns on book equity, $e_{t+j+1} = \log\left(1 + \frac{X_{t+j+1}}{B_{t+j}}\right)$.

Assuming that the earnings growth rate from the sixth year converges to the cross-sectional average of financial analysts' long-term earnings growth rate forecasts (g_t) by year 10 and cash flow payout from the 10th year is a constant proportion (ψ) of ending book equity value (i.e., $B_{t+j+1} = (B_{t+j} + X_{t+j+1})(1-\psi)$ for $j \geq 10$), Da and Warachka (2009) show that the expected sum of discounted future cash flows at time t can be represented in the following way:

$$E_t \sum_{j=0}^{\infty} \rho^j e_{t+j+1} = \sum_{j=0}^{9} \rho^j e_{t,t+j+1} + \frac{\rho^{10}}{1-\rho} \log\left(\frac{1+g_t}{1-\psi}\right). \tag{1}$$

where ρ is an annual log-linearization factor assumed to be 0.95, and ψ is set to 5%. Using financial analysts' earnings forecasts, the expected values of the log book equity return, e_{t+j+1}s, can be estimated as described in Equations (9) - (12) of Da and Warachka (2009)[8].

Once these expected sums of discounted future cash flows are estimated, the expected cash flow news component of unexpected log returns (CFN) is the change in expected CFNs over consecutive months as follows:

$$CFN_t = E_t \sum_{j=0}^{\infty} \rho^j e_{t+j+1} - E_{t-1} \sum_{j=0}^{\infty} \rho^j e_{t+j+1}. \tag{2}$$

After the CFNs are estimated for all sample firms in each month, the following regression is run for each firm in each month using all available data up to the month of systematic CFN estimation:

[8]There is a typo in Equations (11) and (12) of Da and Warachka (2009), with respect to the last term in Equation (1) above.

$$CFN_t^i = \alpha_{CFN}^i + \beta_{CFN}^i CFN_t^{IND} + \epsilon_t^i \quad (3)$$

where CFN_t^{IND} is the value-weighted average CFN of all firms in the same industry with available CFNs where the market capitalization at the end of the most recent fiscal year is used to estimate weights and the industry is defined by the Fama-French 12 industry classification criterion. The slope coefficient, β_{CFN}^i, is defined to be the measure of the systematic cash flow news of a firm (SCFN^i). Once SCFN^is are estimated for each firm in each month, we divide the firms into quartiles (SCFNQ) in each month.[9] More detailed explanations regarding SCFN estimations are available in the Appendix B.

As a way to check whether insiders exploit their access to private information, we estimate abnormal returns following their insider transactions. Since insiders are subject to the short-swing rule, as explained earlier, insiders cannot legally realize high abnormal returns on their stocks over a horizon shorter than a six-month period following their transactions.

Because NPR is measured using insider transactions over the last six months, the abnormal return during the first month after the estimation of NPR is meaningful only to those insiders who traded in the first month of the NPR measurement period. Insiders who traded during the subsequent five months cannot reverse their prior transactions to realize abnormal profits during that month without incurring potential penalties. Therefore, to make sure that all insiders who are captured in the NPR calculation could realize abnormal returns, if they want to do so, without worrying about the short-swing rule, we focus on abnormal performance over six-month horizons following NPR measurements. However, we also examine abnormal performance over one-month horizons to check how firms perform right after the NPR measurement in a short time period.

Over a longer investment horizon, measuring abnormal performance is not straightforward, as no method is free from criticism. Therefore, we use two different approaches to measure abnormal performance to check the sensitivity of the results. In addition, as discussed above, we use the shortest possible investment horizon, the six-month period, among those that are not subject to the restrictions imposed by the short-swing rule to minimize the potential problems arising from the measurement of abnormal performance over longer horizons.

The first approach is to estimate benchmark-adjusted abnormal returns. For this, the performance of the sample firms is compared with the performance of their corresponding

[9]Out of 145,105 final sample observations, there are 36,855 observations in the lowest SCFN quartile and 36,457 observations in the highest SCFNQ as shown in Appendix Table AII. Among those in the lowest (highest) SCFNQ, 16,289 (17,260) observations are in the sell group, while 3,853 (3,490) observations are in the buy group.

size, BM, and momentum-adjusted benchmark portfolios. At the end of June of each year, size, BM and momentum quintiles are formed based on the market capitalization at the end of June, BMs estimated at the most recent fiscal year-end with at least four-month lags, and momentum returns measured based on five-month buy-and-hold returns (BHRs) ending one month prior to the formation.[10] Following Lochstoer and Tetlock (2020), five-month returns instead of 11-month returns are used to define momentum. Since portfolios are rebalanced annually, by defining momentum in this way, one can reflect the finding in Jegadeesh and Titman (1993). They show that with the six-month formation period, the average returns of zero-cost momentum strategies are about 1% regardless of the holding period up to 12 months. In forming size quintiles, we use the cutoff points based only on the NYSE-listed stocks and form BM and momentum quintiles within each size quintile. One-month and six-month buy-and-hold abnormal returns (BHAR_{m1} and BHAR_{m6}, respectively) are calculated by subtracting the BHR of the corresponding size, BM, and momentum portfolios from BHRs of the sample firms.

As an alternative way to measure abnormal performance, abnormal returns are estimated using a calendar-time approach. In each month, we form portfolios that are composed of stocks of the firms that belong to each NPR quartile (and SCFN quartile when needed) during the last one-month or six-month periods ending one month prior to the portfolio formation.[11] Both equally- and value-weighted monthly excess returns over risk-free rates of these calendar-time portfolios are regressed on five factors used in Fama and French (2015) to measure alpha, an abnormal return estimate, of each portfolio.

In addition, we use three different regression approaches to check whether insiders of firms with more systematic cash flow news earn significantly lower returns following their transactions after controlling for firm characteristics. In these regressions, we control for size, BM, momentum, profitability, and investment.

In regression analyses, the key variables of interest are NPR and its interactive variable with SCFNQ_4 and SCFNQ_4 itself, where SCFNQ_4 represents a dummy variable indicating the firms in the highest SCFN quartile (SCFNQ). We use ordinary least squares (OLS) regressions, panel regressions with year- and firm-fixed effects, and two-stage least squares (2SLS) approaches. In the 2SLS approach, NPR and its interactive variable with SCFNQ_4 are assumed to be endogenous, and the median values of these endogenous variables in

[10] Book value of equity is defined as the sum of shareholders' equity (SEQ in Compustat), deferred taxes ($TXDB$) and investment tax credit ($ITCB$) minus preferred stock ($PSTKRV$ if available or $PSTKL$ (or $PSTK$ when both $PSTKRV$ and $PSTKL$ are not available)).

[11] By using six-month periods in the calendar-time approach, the portfolio is composed of stocks with insider transactions up to the maximum of 12 months prior to the return measurement month since the NPR is measured using insider transactions during the prior six-month period ending one month prior to the measurement month.

the industry based on the Fama-French 48-industry classification are used as instrumental variables since they are likely to satisfy both relevance and exclusion criteria.[12] For the OLS approach, Newey-West heteroskedasticity and autocorrelation adjusted standard errors are used to estimate t-statistics, and for the panel and 2SLS results, clustered standard errors at the firm level are used to estimate t-statistics. These two additional approaches are used to reduce endogeneity concerns that arise possibly from omitted variables and/or measurement errors.

B. Data and Summary Statistics

CFNs are estimated using available IBES data from January 1985. The analyst consensus earnings forecasts are from the unadjusted summary file of the Institutional Brokers Estimate System (IBES). Each month, IBES produces these consensus earnings forecasts, typically on the third Thursday of the month.[13] We initially include all unadjusted consensus earnings forecasts between January 1985 and June 2020. The consensus earnings forecasts for the current ($A1_t$) and subsequent fiscal year ($A2_t$), together with its long-term growth forecast (LTG_t), are collected. LTG_t represents an annualized percentage growth rate without explicit forecasting horizons, but it is generally known that the forecasting is for the next three to five years. After estimating CFN by following the procedures in Da and Warachka (2009), which are described in Appendix B, SCFNs are measured by running regressions described above.[14] After estimating SCFN, sample firms are divided into quartiles (SCFNQ) at the end of each month from June 1988 to June 2020.

Insider transactions from January 1988 are collected from the insider trading data cleaned and distributed by Thomson Reuters after being reported to the US SEC according to Section 16(a) of the Securities and Exchange Act of 1934. Starting from June 1988, we measure NPR in each month with at least three insider transactions made by top managers during the past six-month period. We exclude those transactions that involve transaction prices below \$5 in the estimation of NPRs.

The sample is also restricted to those with available stock returns and financial data from

[12]Industry median NPR is likely to be related to NPR given that insiders are on average contrarian investors and stock returns of firms in the same industry tend to move in similar ways (satisfying the relevance criterion) but it is not likely to be closely related to future abnormal performance of sample firms (satisfying the exclusion criterion) as far as the arrival of fundamental news varies across firms within the same industry.

[13]Unadjusted forecasts are used as in Da et al. (2014) because IBES rounds the earnings per share to the nearest cent after a stock split, which can distort some properties of dollar-denominated analyst forecasts, as detailed in Diether, Malloy, and Scherbina (2002).

[14]Since IBES earnings forecasts are mostly available starting from 1985, CFNs can be estimated from 1986 and SCFN from 1988 since at least 24 months' data are required to run regressions.

CRSP and Compustat, respectively. As explained earlier, to focus on insider transactions made by insiders who are likely to possess private information on cash flow news, only those transactions made by C-suite managers, chairmen of the board, directors, officers, presidents, and vice presidents are used to measure NPRs. Transactions included in the analyses are open-market or private purchases and sales of common stock.[15]

After applying all data requirements, 145,105 firm-month observations are in the final sample. The last SCFNQ and NPRQ formations are done at the end of June 2020 so that the last six-month post-quartiles formation performance can be measured in July 2020 using the CRSP stock return data ending in December 2020.

Summary statistics are reported in Table I. To avoid outliers dominating the results, we apply winsorization to all variables at the 1% and 99% thresholds. Appendix A summarizes the methods used to construct each variable. On average, there are about 27 insider transactions in a sample firm per six-month period ending in a month with at least three insider transactions made by top managers during the past six-month period, and the average NPR is -0.59, which is consistent with previous studies showing that there are more insider sales than insider purchase transactions. The average SCFN is 0.34 with the 25^{th} (the 75^{th}) percentile value of 0.00 (0.63).

In Panel B of Table I, across the NPR quartiles, the mean is reported on top and the median is reported in the angle bracket of each cell. There are some significant differences between the purchasing and selling groups. Buyer firms (the fourth NPRQ firms) tend to be smaller than seller firms (the first NPRQ firms), and buyer firms' average BM (0.73) is significantly higher than seller firms' (0.53), which is consistent with insiders being contrarian investors. In addition, buyer firms' profitability is significantly lower (0.24 vs. 0.37) but their investment is similar to seller firms' investment, albeit the difference is significantly different from zero. The average total number of insider transactions of the seller firms (32) is almost three times greater than the average of the buyer firms (16). However, the average SCFN of buyers is similar to that of sellers (0.32 vs. 0.32).

A striking difference between buyer firms and seller firms is observed for the prior one-year return. The average prior one-year gross return for the seller firms is 30.85% while the average for the buyer firm is -0.31%, consistent with insiders being contrarian investors. In contrast, post six-month and one-month BHRs are significantly higher for buyer firms. For example, the average six-month (one-month) BHR for buyer firms is 9.08% (2.07%) while the average for seller firms is 5.46% (0.90%).[16] The mean and median differences between

[15]When shares acquired by the exercise/conversion of derivatives are sold by insiders, insiders report them as open-market or private sales and Thomson Reuters adds a "option-related" sales indicator starting from 1993. We include these sales transactions in the analyses.

[16]In Appendix Table AI, the correlations among key variables are reported. NPR is significantly negatively

buyers and sellers are significantly different from zero at the one percent significance level for all variables examined in Panel B of Table I, except for the mean SCFN. These indicate the necessity of accounting for firm characteristics when evaluating the performance of buyers against that of sellers.

In Appendix Table AII, we compare the characteristics of firms across SCFNQs. Companies in the highest SCFNQ are generally bigger, earn less profit, and engage less in both investment and trading activities. The average NPR of the top SCFNQ firms is greater, while their prior returns are significantly lower compared to the prior returns of the bottom SCFNQ firms. However, the post unadjusted stock returns are not significantly different from each other except for the median post six-month returns.

III. Empirical Results

A. Benchmark-adjusted Abnormal Returns

As a first step to examine abnormal performance of NPRQ firms, equally- and value-weighted average size, BM, and momentum-adjusted buy-and-hold abnormal returns (BHAR) for one year before, and one month and six months after the NPRQ formation date are reported in Table II. Across NPRQs and SCFNQs, each cell displays equally-weighted averages at the top, with value-weighted averages presented in square brackets. Prior one-year BHARs (PBHAR_{y1}) results in Panel A clearly show that the buyer firms have significantly underperformed their benchmarks before the date of NPRQ formation while the sellers have significantly outperformed, and the differences in abnormal performance between buyers and sellers are significant at the one percent significance level. The equally-weighted average PBHAR_{y1} of the seller firms is 7.87% while the average of the buyer firms is -12.30%, both of which are significantly different from zero at the one percent significance level. For value-weighted averages, we find similar results, although the differences are smaller (5.44% vs. -9.88%). Across the SCFN quartiles, the same pattern is observed.

Figure 1 shows the cumulative equally-weighted average monthly size, BM, and momentum-adjusted abnormal returns during the period six months prior to and twelve months after the formation of the NPR quartile. The cumulative average abnormal returns at one month before the formation of the NPR quartile are subtracted from all cumulative average abnormal returns for easier comparisons. Interestingly, buyer firms' cumulative average abnormal

related to size, profitability, investment, total number of insider transactions, and prior returns, while it is significantly positively correlated with BM and future gross returns, BHR_{m6} and BHR_{m1}. In case of SCFN, it is significantly positively correlated with size, NPR and BHR_{m6} but significantly negatively correlated with BM, profitability, investments, the total number of transactions, and prior returns.

returns significantly drop before, while seller firms' cumulative average abnormal returns substantially increase prior to NPR quartile formation months. Following the formation of NPR quartiles, a different pattern starts to emerge. The cumulative average abnormal returns of the buyers increase while the cumulative average monthly abnormal returns of the sellers decrease after the NPR formation dates without reversals.

In Panel B of Table II, the average six-month BHARs following the NPRQ formation date across NPRQs and SCFNQs are reported. The results are quite sensitive to the way averages are calculated. In aggregate, equally-weighted average $BHAR_{m6}$s of buyers are significantly positive. However, they are not significantly different from zero except for the third SCFNQ firms. Even the value-weighted average abnormal return reported in square brackets is marginally significantly positive for those firms in the third SCFNQ firms but is not significant for all other categories. On the other hand, the equally-weighted abnormal returns of sellers are significantly negative across all SCFNQs while their value-weighted average $BHAR_{m6}$s are insignificant in all cases. For the overall sample, the equally-weighted average $BHAR_{m6}$ of the buyer firms is 0.51%, which is significantly different from zero at the one percent significance level, while the value-weighted average is -0.21%, which is not significant. The results are consistent with previous studies showing that insiders of small firms outperform, while insiders of large firms generally do not when they purchase their firms' shares.

Across SCFNQs, for the equally-weighted averages, buyer firms' $BHAR_{m6}$s are significantly higher than the BHARs of the sellers across all SCFNQs except for the second SCFNQ firms, as shown in the last column. However, the value-weighted average abnormal returns exhibit the opposite results for the first and last SCFNQ firms and for the overall sample firms. This indicates that insiders of large firms do not seem to be able to effectively exploit their private information and are likely to base their transactions on other reasons, such as liquidity needs. Interestingly, the magnitude of the equally-weighted average difference among firms in the highest SCFNQ is less than half (and close to a third) of the average difference of the first SCFN quartile firms (0.55% versus 1.61%).

For equally-weighted one-month BHARs reported in Panel C, buyer firms' $BHAR_{m1}$s are significantly positive and the average abnormal returns of the buyers are significantly higher than those of the sellers across all SCFNQs. In addition, sellers significantly underperform their benchmarks in all SCFNQs. For value-weighted one-month BHARs, buyers' $BHAR_{m1}$s are significantly higher than sellers' across all SCFNQs except for the highest SCFNQ firms, although none of them are significantly different from zero when they are examined separately for buyers and sellers.

As emphasized earlier, since the main focus of this paper is to examine whether informed

investors take advantage of opportunities arising directly from private information on cash flow news, equally-weighted average results are more meaningful than in studies that focus on implementable investment implications. In addition, given that sell transactions are likely to be motivated by various non-private information-based reasons, the results of buyer firms are more meaningful in this study.

Overall, the results in Table II indicate that insiders of both small and large firms trade their firms' shares as if they are contrarian investors, but only those of smaller firms seem to be able to earn significant abnormal returns from their inside transactions, possibly because small firms have higher degrees of information asymmetry and/or they have less strict insider trading policies. Across different SCFN quartiles, no obvious differences across SCFNQs are observed even though there is very limited evidence suggesting that insiders in firms within the highest SCFN quartile are less capable of exploiting their informational advantages compared to insiders in other firms.

In Figure 2, cumulative average abnormal returns are compared across NPRQs separately for each SCFNQ. Similar patterns are observed as for the overall sample in all SCFNQs except for the highest SCFN quartile. The buyer firms' cumulative average abnormal returns increase in the month of NPR formation, but they return to close to zero (that is, the level one month prior to the NPRQ formation) and remain close to the cumulative average abnormal returns of other NPRQ firms. This indicates the possibility that insiders of the firms with high systematic CFNs are not able to take advantage of private information as much as those of other firms with less systematic CFNs.

B. Alphas from the Calendar-Time Portfolio Approach

In Table III, we use the calendar-time portfolio approach to check whether observed patterns in abnormal returns are still observed when an alternative measure of abnormal performance is used. As explained earlier, the Fama-French five-factor model is used to see whether buyer firms' excess returns are significantly positive even after controlling for market, size, BM, profitability, and investment factors. For this, in each month from December 1988 to July 2020, equally- and value-weighted portfolios are formed using the stocks of the firms that belong to a particular NPRQ (in Panel A) or NPR and SCFN quartiles (in Panel B) over the past six-month period.[17]

[17]Since the first formation of NPRQ and SCFNQ is done at the end of June 1988, the calendar-time portfolio formation starts from December 1988 so that the calendar-time portfolio includes all those that belong to a particular NPRQ (or NPRQ and SCFNQ) one- to six-month periods ending one month prior to the calendar-time portfolio formation. For a similar reason, the calendar-time portfolio formation ends in July 2020 since the NPRQ and SCFNQ formations stop at the end of June 2020.

The results in Panel A show that for equally-weighted portfolios, significant alpha estimates are observed for both seller and buyer firms (0.24% and 0.73% per month, respectively) but the alpha for the long-short portfolio (long in buyers and short in sellers) is significantly positive, indicating that the alpha for buyers is significantly higher than the alpha for sellers. Contrary to expectation, the alpha estimate is significantly positive only for the value-weighted portfolio of seller firms, while the alpha estimate of the value-weighted long-short portfolio is insignificant. The coefficient estimates of explanatory factors for equally-weighted portfolios suggest that the risk characteristics of seller and buyer firms are similar, except that buyers tend to be more value firms.

In Panel B, the alpha estimates of the sellers and buyers are reported across SCFN quartiles. Similarly to the previous results, alpha estimates of equally-weighted portfolios of buyers are significantly positive across all SCFNQs. For the equally-weighted long-short portfolios, alpha estimates are significant for all SCFNQs, but it is only marginally significant for the highest SCFNQ. Again, the results in Table III show weak evidence that insiders of the firms in the highest SCFNQ are not able to exploit their informational evidence as much as those of other firms.

Appendix Table AIII presents the results for the one-month horizon. Unlike the results for six-month horizons, alpha estimates of buyers and long-short portfolios are all significantly positive at the one percent significance level across all SCFNQs. These results suggest that buyer firms outperform in the short-run even when their cash flow news is very sensitive to industry-wide cash flow news.[18]

Regarding insider sales, unlike the results of benchmark-adjusted abnormal returns, which exhibit significantly negative equally-weighted average abnormal returns of seller firms, the results here show significantly positive, not negative, abnormal returns of seller firms. This conflicting result of seller firms' performance based on two alternative measures is consistent with insider sales being less informative than insider purchases.

In short, focusing on equally-weighted portfolios, the results based on the calendar-time portfolio approach also suggest that insiders of the firms with very sensitive CFNs to industry-wide CFNs do not seem to be able to take advantage of their informational advantages as effectively as those in other firms, although the evidence is weak.

C. Regression Analyses

In this subsection, we use regression analyses to examine whether gross stock returns are higher for buyer firms and whether the performance of the firms in the highest SCFNQ is

[18]Note that for Table AIII, the calendar-time portfolios for one-month horizon are formed from July 1988 to July 2020.

significantly different from others, after controlling for size, BM, momentum, profitability, and investment characteristics. To reduce the concerns arising from endogeneity, we use both panel regressions with firm and year fixed effects and two-stage least squares (2SLS) approaches in addition to OLS regressions. For the 2SLS approach, we consider NPR and its interactive variable with $SCFNQ_4$, an indicator for the highest SCFNQ, as endogenous variables since insider transactions are likely to be affected by past stock price movements and firm characteristics. Here, we use the median values of NPR and its interactive variable with $SCFNQ_4$ (NPR $\times$ $SCFNQ_4$) as instrumental variables since they are likely to satisfy both the relevance and exclusion criteria as explained earlier.

In Table IV, the results for the regression analyses of the post six-month buy-and-hold return (BHR_{m6}) are reported. The coefficient estimates of NPR are significantly positive in all columns, indicating that firms with higher NPR experience significantly higher BHR_{m6}s, while keeping everything else constant. For $SCFNQ_4$s, the coefficient estimate is significantly negative in column 3 where endogeneity concerns are handled using 2SLS, but are not significant in other columns. Regarding $SCFNQ_4$'s interactive variables with NPR, the coefficient estimate is significantly negative in column 3 but the significance disappears when the endogeneity of NPR and its interactive variable with $SCFNQ_4$ is not controlled. The results of the 2SLS approach show that NPR has significantly less positive effects on returns for the highest SCFNQ firms, indicating that insiders of buyer firms in the highest SCFN quartile tend to earn significantly lower returns than those of buyer firms in other SCFNQs after controlling for firm characteristics. This is the most compelling evidence on the significant impact that the characteristics of firms' cash flow news have on the profitability of insider trading.

The results regarding other explanatory variables also depend on the methods used, except for the significantly negative coefficient estimates of prior abnormal returns. The size coefficient estimates are significantly negative except when the OLS is used in column 1, while the signs of the BM coefficients change in columns 2 and 3. In addition, profitability and investment are significant only in the first column. The results are similar when we focus on one-month BHRs in Appendix Table AIV.

In short, regression results in Table IV indicate that the CFN characteristics of an individual firm seem to significantly affect the informativeness of insider trading. The evidence is much stronger than previous results based on benchmark-adjusted abnormal returns and calendar-time portfolio approaches.

For the remainder of the paper, we focus on regression approaches. One of the advantages of using the methods based on abnormal returns is that one can easily estimate the economic magnitude of abnormal profits earned by insiders. However, the point estimates of abnormal

returns and the significance of those estimates, especially for longer horizons, depend a lot on the method used to estimate abnormal returns, as revealed in previous analyses. For this reason, throughout the rest of the paper, we focus on regression methods that are less prone to this issue, despite the advantage of abnormal returns approaches described above. Furthermore, this will enable an examination of the robustness of the most compelling evidence supporting the hypothesis concerning the role of the CFN characteristics.

IV. Robustness Check

In this section, we repeat the regression analyses using subsamples of firms to check whether similar results are found when one focuses on non-routine inside transactions that are known to be more informative. In addition, we further check whether the results are limited to the firms that are likely to have more information asymmetry.

A. Non-routine Insider Transactions

In this subsection, we measure NPRs after excluding routine insider transactions to check the robustness of the regression results documented in Table VI. Cohen et al. (2012) show that only non-routine insider transactions are associated with abnormal returns. To check whether the results hold even when only non-routine transactions are used in measuring NPRs, we follow the method in Cohen et al. (2012) to identify routine insider transactions as described in Subsection II.A.

In Table V, regression analyses are repeated using NPRs based only on non-routine insider transactions, NPR_{NR}. The results are similar to those of Table IV. We also find similar results even if one-month BHRs are used as the dependent variable in Appendix Table AV.

B. Information Asymmetry

In this subsection, we investigate whether the results depend on the informational environment of a firm. For this purpose, we use two proxies to measure the degree of informational asymmetry: size and liquidity. For size, we use the smallest and largest quintile firms based on the NYSE cutoffs, the same quintile firms used to calculate benchmark returns. To measure the liquidity of a firm, we use an illiquidity measure based on bid-ask spreads. In each month, using the CRSP daily returns during the month, we estimate the average bid-ask spread and divide it by the average price to standardize it. We form quintiles based on this illiquidity measure within each size quintile group in each month.

Given that the significant results are found only when the 2SLS approach is used, we report only the 2SLS results in Table VI. The results for small and large firms are reported in the first two columns, and those for low and high liquidity firms (the highest and lowest bid-ask spread illiquidity measure quintile firms, respectively) are reported in the third and fourth columns. The coefficient estimates of NPR are significantly positive in all columns, indicating that buyer firms earn significantly higher returns after controlling for other factors across all categories of firms. However, the coefficient estimates of the interactive variable of NPR and $SCFNQ_4$ are significantly negative only in the first and third columns, where only firms with more asymmetric information are used in the analyses. The results suggest that the characteristics of CFN matter only for those firms that are likely to have more information asymmetry.

V. Conclusion

It seems intuitive to believe that cash flow news is more firm-specific than discount rate news, and, therefore, insiders possess more private information on cash flow news than discount rate news that are likely to be more associated with market-wide factors, as shown in Vuolteenaho (2002). However, Da and Warachka (2009) show that a large part of the cash flow news is systematic.

If a firm's cash flow news is very sensitive to the movement of industry-wide cash flow news, it is unlikely that insiders have large informational advantages regarding future cash flow news of their own firms unless they possess private information on industry-wide cash flow news. Therefore, it is an open question whether the characteristics of cash flow news of a firm affect the informational environment of firms. To shed some light on this issue, this paper investigates whether the profitability of insider trading depends on the characteristics of cash flow news. Although it is illegal for insiders to exploit their informational advantages, they are known to take advantage of their private information. Therefore, the examination of insider trading will help us better understand the issue regarding whether the characteristics of a firm are associated with its informational environment.

The paper presents some evidence that insiders of firms with cash flow news that are more sensitive to industry-wide cash flow news earn significantly lower abnormal returns than those of firms with less sensitive cash flow news. However, it turns out that this conclusion mainly applies to those firms that are more likely to have higher information asymmetry, such as small firms and firms with stocks that have low liquidity.

The results suggest that when a firm is subject to high information asymmetry, the characteristics of cash flow news of the firm can help us evaluate the degree of information

asymmetry of the company. Insiders of the firms with high degrees of asymmetric information are likely to possess a large amount of private information in general, but when their firms' cash flows is very sensitive to industry-wide cash flows, their informational advantages might be limited since their cash flow news depends a lot on industry-wide cash flow news. Therefore, unless they also possess private information on industry-wide news, they are not likely to earn as much abnormal profits as those of the firms with less sensitive cash flow news.

In summary, the paper presents evidence on the possibility that the characteristics of cash flow news affect the informational environment of a firm using top managers' personal transactions on their own firms' stocks. It will be interesting to explore how the attributes of cash flow news affect corporate decisions, such as equity issuing and buying back decisions, which are known to take into account stock misvaluation.

Appendix A. Variable definitions

Variables	Definitions*
Size ($ mil)	Market capitalization in 2020 US $millions at the end of the fiscal year prior to the benchmark portfolio formation in June of each year with at least a four-month lag.
BM	Book-to-market equity ratio based on the book value of equity and market capitalization at the fiscal year-end. Book equity is defined as the sum of shareholder's equity (SEQ), deferred taxes ($TXDB$) and investment tax credit ($ITCB$) minus preferred stock. Preferred stock value is estimated based on the redemption value ($PSTRV$), liquidation value ($PSTKL$), or total preferred stock value ($PSTK$), whichever is available first in the order written.
Profitability	Profitability is defined as total revenue ($REVT$) minus cost of goods sold ($COGS$) over total assets (AT).
Investment	Investment is defined as the change in total assets (AT) over total assets at the end of the previous fiscal year.
# of Tran	Total number of transactions is the sum of the number of open-market/private purchases and the number of open-market/private sales transactions made by top managers during the six-month period ending at the month end when a net purchase ratio is estimated. Top managers include C-suite managers, chairmen of the board, directors, officers, presidents, and vice presidents who are required to report their transactions of their firms' stocks to the US Securities and Exchange Commission (SEC).
NPR/NPRQ	In each month, net purchase ratio (NPR) is calculated as the number of open-market/private purchases minus the number of open-market/private sales divided by the total number of transactions made by top managers during the past six-month period. When the total number of transactions during the six-month NPR estimation period is less than three, NPR is set to be missing. NPR quartiles (NPRQs) are formed using absolute cutoff values of -0.95, 0, and 0.95 in each month.

CFN/SCFNQ	CFN represents cash flow news (CFN) that is estimated using the method described in Da and Warachka (2009) and Da et al. (2014). SCFN is defined as the coefficient from a regression of an individual firm's CFN on the value-weighted average CFN of all firms in the same industry, where industries are defined using the Fama-French 12 industry classification. The regression uses all available data up to the month of SCFN calculation, with a minimum of 24 monthly observations. SCFNQ is the quartiles of SCFN and is formed each month. Details are explained in Appendix B.
$\text{BHR}_{m6}/\text{BHR}_{m1}(\%)$	Six-month and one-month buy-and-hold returns starting from the month after the NPR calculation.
$\text{PBHAR}_{y1}(\%)$	Prior one-year size, BM and momentum-adjusted buy-and-hold abnormal returns ending at the month when the NPR is estimated. Size, BM and momentum benchmark quintile portfolios are formed in June of each year based on the market capitalization in June of the formation year, book-to-market equity ratio estimated at the most recent fiscal year-end with at least four-month lags, and prior five-month buy-and-hold returns ending one month prior to the quintile formation, respectively. The size quintiles are formed using cutoff points based only on NYSE stocks. BM and momentum quintiles are formed within each size quintile.
$\text{BHAR}_{m6}/\text{BHAR}_{m1}(\%)$	Six-month and one-month size, BM, and momentum-adjusted buy-and-hold abnormal returns starting from the month after the estimation of NPR. Size, BM, and momentum benchmark portfolios are formed as explained above for PBHAR_{y1}.
Market, SMB HML, RMW CMA	Market, SMB, HML, RMW, and CMA are market, size, value, profitability, and investment factors defined and available at the Ken French's website, `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

*Stock return data are from CRSP, financial data are from annual Compustat, and earnings forecasts used to estimate CFNs are from the IBES database files. The names of the compustat items are in parentheses. All financial data are used from the end of June after the end of the fiscal year with at least a four-month lag.

Appendix B. CFN and SCFN quartiles

Cash flow news is estimated using the method described in Da and Warachka (2009) and Da et al. (2014). Da and Warachka (2009) estimate the cash flow news (CFN) using the decomposition of unexpected log returns into cash flow news and discount rate news in Campbell and Shiller (1988) together with the clean-surplus accounting identity as in Vuolteenaho (2002). CFNs are estimated in each month using the last earnings forecast summary available during the month in the IBES statistical period, that is, the date the set of summary statistics is calculated. Earnings per share (EPS) forecasts for one- and two-year forecasting periods, as well as long-term EPS growth rate forecasts, are collected from the IBES Unadjusted Summary History - Summary Statistics file ("statsumu_epsus" file in WRDS). IBES reports earnings forecasts each month, and we collect the required data each month for all firms.

The sample is restricted to those with the available earnings forecast data for the current fiscal year ($A1_t$), the next fiscal year ($A2_t$), and the long-term EPS growth forecast (LTG_t) from IBES. As described in Equation (2) in Da et al. (2014), in each month, expected earnings over the next five years are estimated using financial analysts' earnings per share (EPS) forecasts as well as long-term EPS growth rate forecasts. For the first two fiscal years, the IBES earnings forecasts are used to estimate expected earnings (i.e., $X_{t,t+1} = A1_t$ and $X_{t,t+2} = A2_t$, where $X_{t,t+1}$ is the expected earnings for fiscal year $t+1$ at time t). From the third to fifth year, LGT_t is used to estimate the expected earnings. For example, $X_{t,t+3}$ is $X_{t,t+2} \times (1 + LTG_t) = A2_t \times (1 + LTG_t)$.

For years from six to 10, expected earnings are estimated using Equation (3) in Da et al. (2014) (that is, $X_{t,t+j+1} = X_{t,t+j}\left[1 + LTG_t + \frac{j-4}{5}(g_t - LTG_t)\right]$, for $5 \leq j \leq 9$) assuming that the expected earnings growth rate converges to the cross-sectional average long-term EPS growth rate forecasts, g_t, by year 10. Finally, assuming that the cash flow payout is equal to 5% of the ending-period book value (that is, $B_{t,t+j+1} = (B_{t,t+j} + X_{t,t+j+1}) \times (1 - 0.05)$), one plus the expected accounting return (earnings over the book value) converges to $\frac{1+g_t}{1-0.05}$. Then, the expected log accounting return at time t can be defined as follows as in Eq (4) of Da et al. (2014):

$$e_{t,t+j+1} = \begin{cases} \log\left(1 + \frac{X_{t,t+j+1}}{B_{t,t+j}}\right) & \text{for } 0 \leq j \leq 9, \\ \log\left(\frac{1+g_t}{1-0.05}\right) & \text{for } j \geq 10, \end{cases}$$

where X_{t+j+1} is the $j+1$ period ahead earnings forecast made at time t, $B_{t,t+j}$ is the j period ahead expected book equity value at time t, and g_t is the cross-sectional average of long-term

earnings growth rate at time t.[19] Consequently, the expected cash flow component of return is:

$$E_t \sum_{j=0}^{\infty} 0.95^j e_{t+j+1} = \sum_{j=0}^{9} 0.95^j e_{t,t+j+1} + \frac{0.95^{10}}{1-0.95} \log\left(\frac{1+g_t}{1-0.05}\right).$$

where the annual log-linearization factor (ρ) is assumed to be 0.95. Finally, the cash flow news (CFN) is defined as:

$$CFN_t = E_t \sum_{j=0}^{\infty} 0.95^j e_{t+j+1} - E_{t-1} \sum_{j=0}^{\infty} 0.95^j e_{t+j+1}.$$

As in Da and Warachka (2009), to eliminate outlier effects, earnings forecasts and book equity values, as well as predicted long-term growth rates, are winorized at their 1st and 99th percentiles each month.

Once CFNs are estimated for each stock in each month, the following regression is run using all data available at the time of estimation:

$$CFN_t^i = \alpha_{CFN}^i + \beta_{CFN}^i CFN_t^{IND} + \epsilon_t^i$$

where CFN_t^{IND} is the value-weighted average CFN of all firms in the same industry defined by the Fama-French 12 industrial classification criterion with available CFN values in month t. In each month, the coefficient estimate of CFN_t^{IND}, β_{CFN}^i from the above regression, is the measure of systematic cash flow news, SCFN, and the SCFN quartiles are formed based on the SCFNs of all available sample firms in each month.

[19] As noted earlier, there is a typo in Da and Warachka (2009) and the correct one is $log\left(\frac{1+g_t}{1-0.05}\right)$ for $j \geq 10$ as above

Appendix C. Appendix Tables

Table AI
Correlation

This table reports correlations among key variables used in the paper. The sample covers insider transactions during January 1988 and June 2020 made by top managers of NYSE, Amex and Nasdaq firms with available earnings forecast data from IBES and required return and financial data available from CRSP and Compustat, respectively. Market capitalization is the inflation-adjusted market capitalization in 2020 $US at the end of fiscal year. NPR is the number of buy transactions minus the number of sell transactions divided by the total number of transactions made by top managers over the past six-month period. Appendix A describes how each variable is constructed. Bold numbers represent significant correlations at least at the 10% significance level.

	Size	BM	Profit	Inv	# of Tran	NPR	SCFN	$PBHR_{y1}$	BHR_{m6}	BHR_{m1}
Size($ mil)	1.000									
BM	**-0.19**	1.000								
Profit	**0.03**	**-0.32**	1.000							
Inv	0.00	**-0.17**	**0.01**	1.000						
# of Tran	**0.10**	**-0.09**	**0.08**	**0.05**	1.000					
NPR	**-0.11**	**0.16**	**-0.18**	**-0.02**	**-0.17**	1.000				
SCFN	**0.31**	**-0.05**	**-0.06**	**-0.03**	**-0.01**	**0.01**	1.000			
$PBHR_{y1}$	**-0.06**	**0.08**	**0.09**	**-0.03**	**0.11**	**-0.25**	**-0.03**	1.000		
BHR_{m6}	**-0.01**	**0.03**	**0.01**	**-0.03**	**-0.05**	**0.05**	**0.01**	**-0.02**	1.000	
BHR_{m1}	**-0.01**	**0.02**	**0.01**	**-0.01**	**-0.02**	**0.04**	0.00	**-0.01**	**0.38**	1.000

Table AII

Summary Statistics Across SCFN Quartiles

The sample covers insider transactions made by top managers of NYSE, Amex and Nasdaq firms during January 1988 and June 2020 with available earnings forecast data from IBES and stock return and financial data in CRSP and Compustat, respectively. SCFN represents the systematic cash flow news, which captures how sensitive an individual firm's cash flow news (CFN) is to the value-weighted industry average CFN. Appendix A describes how each variable is constructed. In each cell, mean is reported on top and median is reported in angle brackets. ***, **, * indicate that reported average or median of the highest SCFNQ is significantly different from that of the lowest SCFNQ at the one, five and 10 percent significance levels, respectively. The number of observations in each SCFNQ is reported in parentheses under column headers. To avoid outliers dominating the results, all firm-level variables are winsorized at the one and 99% levels.

	Low (36,855)	2 (36,081)	3 (35,711)	High (36,457)
Size(2020 $ mil)	5,078 ⟨1,175⟩	9,107 ⟨2,144⟩	9,730 ⟨2,185⟩	14,341*** ⟨2,041⟩***
BM	0.58 ⟨0.49⟩	0.54 ⟨0.45⟩	0.55 ⟨0.47⟩	0.58 ⟨0.51⟩***
Profitability	0.35 ⟨0.33⟩	0.39 ⟨0.36⟩	0.35 ⟨0.31⟩	0.27*** ⟨0.22⟩***
Investment	0.15 ⟨0.09⟩	0.13 ⟨0.08⟩	0.13 ⟨0.08⟩	0.12*** ⟨0.08⟩***
# of tran	26.68 ⟨13.00⟩	27.90 ⟨13.00⟩	26.69 ⟨12.00⟩	25.38*** ⟨12.00⟩***
NPR	-0.57 ⟨-1.00⟩	-0.65 ⟨-1.00⟩	-0.59 ⟨-1.00⟩	-0.53*** ⟨-0.96⟩***
SCFN	-0.19 ⟨-0.20⟩	0.33 ⟨0.22⟩	0.49 ⟨0.35⟩	0.75*** ⟨0.59⟩***
$PBHR_{y1}(\%)$	25.48 ⟨17.59⟩	24.84 ⟨17.69⟩	22.56 ⟨16.78⟩	20.93*** ⟨15.79⟩***
$BHR_{m6}(\%)$	6.08 ⟨4.71⟩	6.21 ⟨4.98⟩	6.41 ⟨5.35⟩	6.21 ⟨5.33⟩***
$BHR_{m1}(\%)$	1.09 ⟨0.97⟩	1.11 ⟨0.99⟩	1.09 ⟨1.00⟩	1.08 ⟨0.94⟩

Table AIII
Calendar-time Portfolio Performance: One-month Horizon

This table reports the results of the Fama-French five-factor model for calendar-time portfolios to examine abnormal performance over one-month horizons after the formation of NRP quartiles. Calendar-time portfolios are formed in each month during July 1988 and July 2020, and composed of the stocks that belong to the corresponding NPRQ (or NPRQ and SCFNQ) during the past one-month period prior to the portfolio formation. Details on the construction of NPRQ and SCFNQ are described in Appendix A and Subsection II.A. Sell and Buy represent the first ($NPRQ_1$) and fourth ($NPRQ_4$) NPR quartiles, respectively, and Buy-Sell represents a portfolio which takes a long position in $NPRQ_4$ and a short position in $NPRQ_1$. All five-factor values are from the Ken French's website. Market, SMB, HML, RMW, and CMA are market, size, value, profitability, and investment factors, respectively. In each cell, coefficient estimates are reported on top and t-statistics based on Newey-West's heteroscedasticity and autocorrelation robust standard errors with four lags are reported in parentheses. In Panel B, the estimates of the intercept are reported. ***, **, * indicate that reported coefficient estimates are significantly different from zero at the one, five and 10 percent significance levels, respectively.

	equally-weighted portfolio			Value-weighted portfolio		
	Sell	Buy	Buy-Sell	Sell	Buy	Buy-Sell
Panel A: All						
Alpha	0.171**	0.988***	0.812***	0.231**	0.453**	0.218
	(2.55)	(7.87)	(6.15)	(2.35)	(2.54)	(1.13)
Market	1.004***	0.899***	-0.105***	0.995***	1.065***	0.069
	(41.55)	(24.66)	(-3.22)	(35.89)	(17.96)	(1.19)
SMB	0.481***	0.562***	0.080	-0.013	0.193**	0.207***
	(16.65)	(9.00)	(1.50)	(-0.39)	(2.41)	(2.58)
HML	-0.040	0.481***	0.524***	-0.160***	0.527***	0.688***
	(-1.16)	(6.90)	(8.25)	(-3.85)	(4.47)	(6.01)
RMW	0.242***	0.216**	-0.028	0.058	0.165	0.106
	(6.76)	(2.39)	(-0.33)	(1.26)	(1.44)	(0.97)
CMA	0.076	0.030	-0.047	-0.045	0.201	0.245
	(1.25)	(0.32)	(-0.48)	(-0.65)	(1.15)	(1.46)
# of months	385	383	383	385	383	383
R^2	0.93	0.81	0.33	0.86	0.64	0.30
Panel B: Alphas for SCFN Quartiles						
Low	0.202**	0.848***	0.646***	0.381***	0.274	-0.103
	(1.97)	(3.94)	(2.67)	(2.59)	(1.18)	(-0.37)
2	0.049	1.008***	0.958***	0.246	0.602**	0.354
	(0.42)	(5.37)	(4.55)	(1.42)	(2.14)	(1.05)
3	0.184**	1.261***	1.066***	0.308**	0.740***	0.446
	(1.97)	(6.48)	(5.00)	(2.17)	(2.65)	(1.46)
High	0.288***	0.855***	0.561***	0.229**	0.683***	0.441
	(3.58)	(4.47)	(2.88)	(2.20)	(2.65)	(1.58)

Table AIV

Regression Results: One-month Returns

This table reports the results of regression analyses for one-month stock returns (BHR_{m1}). Three approaches are used. The results of ordinary least squares regressions are reported under the OLS column and those of panel regressions with year and firm fixed effects are reported under the Panel column. Under the 2SLS column, the results based on the two-stage least squares method are reported. NPR and NPR × $SCFNQ_4$ are assumed to be endogenous, and Fama-French 48 industry median values of those are used as instrumental variables in this approach. Here, $SCFNQ_4$ represents a dummy variable indicating the firms belonging to the fourth SCFN quartile. Detailed definitions of other variables are available in Appendix A. The coefficients are reported on top and t-statistics are reported in parentheses. In calculating t-statistics, Newey and West's heteroskedasticity and autocorrelation-adjusted standard errors are used for OLS results, and clustered standard errors at the firm level are used for Panel and 2SLS results. ***, **, * indicate that reported coefficient estimates are significantly different from zero at the one, five and 10 percent significance levels, respectively.

	OLS	Panel	2SLS
NPR	0.443***	0.787***	2.801***
	(8.86)	(11.98)	(8.56)
$SCFNQ_4$	0.008	-0.039	-1.202***
	(0.11)	(-0.42)	(-2.96)
NPR × $SCFNQ_4$	-0.016	-0.037	-2.147***
	(-0.19)	(-0.38)	(-2.99)
ln(Size)	-0.083***	-1.600***	-1.520***
	(-5.20)	(-19.52)	(-17.80)
BM	0.324***	-0.378**	-0.485***
	(4.04)	(-2.33)	(-2.92)
$PBHAR_{y1}$	-0.008***	-0.016***	-0.012***
	(-8.26)	(-15.49)	(-9.74)
Profit	0.827***	0.310	0.576
	(7.28)	(0.78)	(1.43)
Investment	-0.312**	-0.187	-0.136
	(-2.15)	(-1.09)	(-0.78)
Firm fixed effect	No	Yes	Yes
Year fixed effect	No	Yes	Yes
# of obs	145,093	145,093	145,093
R^2	0.003	0.009	0.036

Table AV

Regression Results of Non-Routine Insider Transactions: One-month Returns

This table reports the results of regression analyses for one-month stock returns (BHR_{m1}). In calculating NPR, routine transactions defined by Cohen et al. (2012) are excluded here. Three approaches are used. The results of ordinary least squares regressions are reported under the OLS column and those of panel regressions with year and firm fixed effects are reported under the Panel column. Under the 2SLS column, the results based on the two-stage least squares method are reported. NPR and NPR × $SCFNQ_4$ are assumed to be endogenous, and Fama-French 48 industry median values of those are used as instrumental variables in this approach. Here, $SCFNQ_4$ represents a dummy variable indicating the firms belonging to the fourth SCFN quartile. Detailed definitions of other variables are available in Appendix A. The coefficients are reported on top and *t*-statistics are reported in parentheses. In calculating *t*-statistics, Newey and West's heteroskedasticity and autocorrelation-adjusted standard errors are used for OLS results, and clustered standard errors at the firm level are used for Panel and 2SLS results. ***, **, * indicate that reported coefficient estimates are significantly different from zero at the one, five and 10 percent significance levels, respectively.

	OLS	Panel	2SLS
NPR_{NR}	1.801***	0.855***	1.991***
	(8.37)	(10.84)	(5.35)
$SCFNQ_4$	0.216	-0.161	-1.128**
	(0.65)	(-1.42)	(-2.17)
NPR_{NR}× $SCFNQ_4$	0.216	-0.095	-1.656**
	(0.59)	(-0.85)	(-2.00)
ln(Size)	-0.014	-1.616***	-1.580***
	(-0.19)	(-16.95)	(-16.38)
BM	2.185***	-0.451**	-0.508***
	(5.92)	(-2.35)	(-2.64)
$PBHAR_{y1}$	-0.017***	-0.016***	-0.014***
	(-4.37)	(-13.79)	(-10.91)
Profit	3.087***	0.249	0.326
	(5.86)	(0.55)	(0.73)
Investment	-2.070***	-0.147	-0.148
	(-3.22)	(-0.76)	(-0.76)
Firm fixed effect	No	Yes	Yes
Year fixed effect	No	Yes	Yes
# of obs	114,248	114,248	114,248
R^2	0.005	0.009	0.045

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Table I
Summary Statistics

The sample covers insider transactions made by top managers of NYSE, Amex and Nasdaq firms during January 1988 and June 2020 with available earnings forecast data from IBES and stock return and financial data in CRSP and Compustat, respectively. NPR is the number of buy transactions minus the number of sell transactions divided by the total number of transactions over the past six-month period and NPR quartiles (NPRQs) are formed based on absolute cutoff points of -0.95, 0.0 and 0.95. Appendix A describes how each variable is constructed. In Panel B, mean is reported on top and median is reported in angle brackets. In the last column of Panel B, ***, **, * indicate that reported average or median of Buy (the highest NPRQ) is significantly different from that of Sell (the lowest NPRQ) at the one, five and 10 percent significance levels, respectively. The number of observations in each NPRQ is reported in parentheses under column headers in Panel B. To avoid outliers dominating the results, all firm-level variables are winsorized at the one and 99% levels.

Panel A: Total sample

	# of Obs	Mean	Median	SD	25%	75%
Size(2020 $ mil)	145,105	9,553	1,798	25,011	584	6,438
BM	145,105	0.56	0.48	0.39	0.29	0.72
Profitability	145,105	0.34	0.31	0.25	0.13	0.49
Investment	145,105	0.13	0.08	0.21	0.02	0.18
# of Tran	145,105	26.66	12.00	46.81	6.00	25.00
NPR	145,105	-0.59	-1.00	0.65	-1.00	-0.40
$SCFN$	145,105	0.34	0.28	0.57	0.00	0.63

Panel B: NPR Quartile

	Sell (77,031)	2 (40,158)	3 (13,602)	Buy (14,314)
Size(2020 $ mil)	10,703 ⟨2,137⟩	11,056 ⟨2,199⟩	5,484 ⟨1,189⟩	3,011*** ⟨0,645⟩***
BM	0.53 ⟨0.44⟩	0.54 ⟨0.47⟩	0.63 ⟨0.56⟩	0.73*** ⟨0.65⟩***
Profitability	0.37 ⟨0.34⟩	0.33 ⟨0.30⟩	0.28 ⟨0.21⟩	0.24*** ⟨0.15⟩***
Investment	0.13 ⟨0.08⟩	0.14 ⟨0.09⟩	0.13 ⟨0.08⟩	0.12*** ⟨0.07⟩***
# of tran	32.41 ⟨14.00⟩	24.92 ⟨13.00⟩	10.53 ⟨7.00⟩	15.91*** ⟨9.00⟩***
NPR	-1.00 ⟨-1.00⟩	-0.64 ⟨-0.69⟩	0.31 ⟨0.33⟩	0.95*** ⟨1.00⟩***
SCFN	0.32 ⟨0.25⟩	0.38 ⟨0.32⟩	0.37 ⟨0.31⟩	0.32 ⟨0.28⟩***
$PBHR_{y1}$(%)	30.85 ⟨22.30⟩	22.63 ⟨16.27⟩	9.06 ⟨6.12⟩	-0.31*** ⟨-2.63⟩***
BHR_{m6}(%)	5.46 ⟨4.54⟩	6.18 ⟨5.14⟩	7.71 ⟨6.34⟩	9.08*** ⟨7.01⟩***
BHR_{m1}(%)	0.90 ⟨0.90⟩	1.00 ⟨0.90⟩	1.42 ⟨1.16⟩	2.07*** ⟨1.41⟩***

Table II
Equally- and Value-weighted Average Abnormal Returns

This table reports equally- and value-weighed average size, BM and momentum-adjusted buy-and-hold abnormal returns (BHARs) of NPR quartiles (NPRQs) over one-year prior to and six- and one-month periods following NPRQ formation months In each cell, equally-weighted average BHARs are reported on top and value-weighted average BHARs are reported in square brackets. $PBHAR_{y1}$ is one-year BHAR prior to the formation of NPRQ and $BHAR_{m6}$ and $BHAR_{m1}$ are six-month and one-month BHARs following the NPRQ formation date, respectively. Net purchase ratios (NPRs) are defined as the ratio of the number of buy transactions minus the number of sell transactions over the total number of buy and sell transactions made by top managers during the past six-month period and estimated at the end of each month with at least three insider transactions over the past six-month period. To capture the sensitivity of individual firms' cash flow news (CFN) to industy-wide CFN, SCFN is estimated at the end of each month using the method explained in Appendix B. ***, **, * indicate that reported average are significantly different from zero at the one, five and 10 percent significance levels, respectively.

SCFN Quartile	NPR Quartile				
	Sell	2	3	Buy	Buy-Sell
Panel A: $PBHAR_{y1}$ (%)					
Low	10.216***	2.941***	-6.643***	-12.501***	-22.717***
	[9.278]***	[3.985]***	[−4.705]***	[−11.722]***	[−21.000]***
2	7.901***	3.281***	-7.475***	-13.825***	-21.726***
	[6.938]***	[2.590]***	[−6.918]***	[−10.535]***	[−17.473]***
3	7.043***	2.244***	-5.765***	-13.571***	-20.613***
	[4.123]***	[0.457]***	[−2.910]***	[−11.259]***	[−15.382]***
High	6.039***	1.557***	-5.288***	-10.050***	-16.089***
	[3.698]***	[−1.171]***	[−7.187]***	[−8.222]	[−11.919]***
All	7.868***	2.481***	-6.208***	-12.303***	-20.171***
	[5.444]***	[0.757]	[−5.681]***	[−9.875]***	[−15.320]***
Panel B: $BHAR_{m6}$(%)					
Low	-1.240***	-0.051	-0.348	0.367	1.606***
	[0.210]	[−0.632]	[−2.189]	[−1.406]	[−1.616]***
2	-0.524***	-0.604***	0.159	0.151	0.675
	[0.269]	[−0.801]	[−0.063]	[0.612]	[0.343]
3	-0.344***	0.084	-0.401	1.397***	1.741***
	[0.277]	[0.053]	[−1.212]	[1.131]*	[0.854]**
High	-0.388***	-0.230	0.245	0.162	0.550*
	[0.252]	[−0.071]	[0.282]*	[−0.774]	[−1.026]***
All	-0.635***	-0.202**	-0.080	0.511***	1.146***
	[0.256]	[−0.277]	[−0.508]	[−0.213]	[−0.469]***
Panel C: $BHAR_{m1}$(%)					
Low	-0.395***	-0.149*	0.096	0.501***	0.896***
	[−0.140]	[−0.316]	[−0.346]	[0.267]	[0.407]***
2	-0.224***	-0.210***	-0.050	0.542***	0.765***
	[−0.119]	[−0.210]	[−0.239]	[0.232]	[0.351]**
3	-0.206***	-0.157**	-0.039	0.758***	0.965***
	[−0.053]	[−0.087]	[−0.557]	[0.290]	[0.343]**
High	-0.191***	-0.129*	0.108	0.519***	0.710***
	[0.020]	[−0.255]	[−0.038]	[−0.117]	[−0.137]
All	-0.257***	-0.161***	0.035	0.575***	0.832***
	[−0.057]	[−0.209]**	[−0.252]	[0.097]	[0.154]**

Table III
Calendar-time Portfolio Performance: Six-month Horizon

This table reports the results of the Fama-French five-factor model for calendar-time portfolios to test abnormal performance over six-month horizons following NPR estimation. Calendar-time portfolios are formed in each month during December 1988 and July 2020 and composed of the stocks that belong to the corresponding NPR (or NPR and SCFN) quartiles during the past six-month period ending one month prior to the portfolio formation. Details on the definitions of NPR and SCFN are described in Appendix A. Sell and Buy represent the first ($NPRQ_1$) and fourth ($NPRQ_4$) NPR quartiles, respectively, and Buy-Sell represents a portfolio that takes a long position in $NPRQ_4$ and a short position in $NPRQ_1$. All five-factor values are from the Ken French's website. SMB, HML, RMW, and CMA are size, value, profitability, and investment factors, respectively. In each cell, coefficient estimates are reported on top and t-statistics based on Newey-West's heteroscedasticity and autocorrelation robust standard errors with four lags are reported in parentheses. In Panel B, the estimates of the intercept are reported. ***, **, * indicate that reported coefficient estimates are significantly different from zero at the one, five and 10 percent significance levels, respectively.

	Equally-weighted Portfolio			Value-weighted portfolio		
	Sell	Buy	Buy-Sell	Sell	Buy	Buy-Sell
Panel A: All						
Alpha	0.240***	0.726***	0.483***	0.275***	0.079	-0.195
	(3.91)	(6.58)	(4.42)	(3.29)	(0.51)	(-1.14)
Market	1.012***	0.900***	-0.112***	1.001***	1.051***	0.050
	(41.47)	(25.57)	(-3.78)	(40.80)	(19.51)	(0.93)
SMB	0.463***	0.543***	0.079**	-0.018	0.090	0.107
	(13.73)	(10.09)	(2.03)	(-0.50)	(1.19)	(1.43)
HML	-0.009	0.518***	0.529***	-0.160***	0.528***	0.688***
	(-0.25)	(8.19)	(10.74)	(-4.52)	(5.31)	(7.12)
RMW	0.272***	0.216***	-0.057	0.101***	0.164*	0.063
	(7.04)	(2.80)	(-0.96)	(2.70)	(1.72)	(0.70)
CMA	0.065	-0.011	-0.077	-0.020	0.051	0.071
	(1.11)	(-0.12)	(-0.93)	(-0.37)	(0.33)	(0.48)
# of months	380	379	379	380	379	379
R^2	(0.94)	(0.85)	(0.41)	(0.89)	(0.69)	(0.31)
Panel B: Alphas for SCFN Quartiles						
Low	0.275***	0.684***	0.403**	0.391***	0.212	-0.185
	(3.03)	(4.48)	(2.43)	(2.71)	(1.20)	(-0.82)
2	0.226**	0.765***	0.538***	0.550***	0.131	-0.419
	(2.52)	(4.79)	(3.31)	(3.71)	(0.56)	(-1.51)
3	0.247***	0.848***	0.591***	0.483***	0.172	-0.300
	(3.02)	(5.57)	(3.69)	(4.38)	(0.78)	(-1.24)
High	0.351***	0.594***	0.245*	0.242**	-0.006	-0.245
	(5.02)	(3.91)	(1.71)	(2.50)	(-0.03)	(-1.09)

Table IV

Regression Results: BHR_{m6}

This table reports the results of regression analyses for six-month buy-and-hold returns (BHR_{m6}s). Three approaches are used. The results of ordinary least squares (OLS) regressions are reported under the OLS column and those of panel regressions with year and firm fixed effects are reported under the Panel column. Under the 2SLS column, the results based on the two-stage least squares method are reported. NPR and NPR × $SCFNQ_4$ are assumed to be endogenous and Fama-French 48 industry median values of those are used as instrumental variables in this approach. Here, $SCFNQ_4$ is a dummy variable indicating the highest SCFN quartile. Detailed definitions of other variables are available in Appendix A. The coefficient estimates are reported on top and t-statistics are reported in parentheses. In calculating t-statistics, Newey and West's heteroskedasticity and autocorrelation-adjusted standard errors are used for OLS results, and clustered standard errors at the firm level are used for Panel and 2SLS results. ***, **, * indicate that reported coefficient estimates are significantly different from zero at the one, five and 10 percent significance levels, respectively.

	OLS	Panel	2SLS
NPR	1.599***	3.124***	11.712***
	(8.50)	(12.34)	(10.43)
$SCFNQ_4$	0.140	-0.360	-5.021***
	(0.50)	(-0.96)	(-3.64)
NPR × $SCFNQ_4$	0.128	-0.251	-8.715***
	(0.40)	(-0.65)	(-3.65)
ln(Size)	-0.065	-8.472***	-8.127***
	(-0.98)	(-21.69)	(-20.12)
BM	2.122***	-1.920***	-2.384***
	(6.48)	(-2.73)	(-3.31)
$PBHAR_{y1}$	-0.017***	-0.064***	-0.045***
	(-4.83)	(-15.35)	(-9.49)
Profit	3.384***	-0.674	0.496
	(7.12)	(-0.37)	(0.27)
Investment	-2.296***	-1.086	-0.857
	(-3.94)	(-1.49)	(-1.16)
Firm fixed effect	No	Yes	Yes
Year fixed effect	No	Yes	Yes
# of obs	145,093	145,093	145,093
R^2	0.005	0.037	0.148

Table V

Regression Results of Non-Routine Transactions: BHR_{m6}

This table reports the results of regression analyses for six-month buy-and-hold returns (BHR_{m6}s). Three approaches are used. Here, NPRs are calculated using only non-routine insider transactions defined by Cohen et al. (2012). The results of ordinary least squares (OLS) regressions are reported under the OLS column and those of panel regressions with year and firm fixed effects are reported under the Panel column. Under the 2SLS column, the results based on the two-stage least squares method are reported. NPR_{NR} and NPR_{NR} $\times$ $SCFNQ_4$ are assumed to be endogenous and Fama-French 48 industry median values of those are used as instrumental variables in this approach. Here, $SCFNQ_4$ is a dummy variable indicating the highest SCFN quartile. Detailed definitions of other variables are available in Appendix A. The coefficient estimates are reported on top and *t*-statistics are reported in parentheses. In calculating *t*-statistics, Newey and West's heteroskedasticity and autocorrelation-adjusted standard errors are used for OLS results, and clustered standard errors at the firm level are used for Panel and 2SLS results. ***, **, * indicate that reported coefficient estimates are significantly different from zero at the one, five and 10 percent significance levels, respectively.

	OLS	Panel	2SLS
NPR_{NR}	1.801***	3.368***	12.673***
	(8.37)	(11.52)	(14.94)
$SCFNQ_4$	0.216	-0.474	-7.438***
	(0.65)	(-1.07)	(-6.19)
$NPR_{NR}\times$ $SCFNQ_4$	0.216	-0.344	-11.600***
	(0.59)	(-0.78)	(-6.13)
ln(Size)	-0.014	-8.857***	-8.537***
	(-0.19)	(-20.42)	(-41.84)
BM	2.185***	-2.469***	-2.959***
	(5.92)	(-3.16)	(-6.92)
$PBHAR_{y1}$	-0.017***	-0.067***	-0.050***
	(-4.37)	(-14.89)	(-16.88)
Profit	3.087***	-1.431	-0.696
	(5.86)	(-0.72)	(-0.69)
Investment	-2.070***	-0.865	-0.832*
	(-3.22)	(-1.09)	(-1.87)
Firm fixed effect	No	Yes	Yes
Year fixed effect	No	Yes	Yes
# of obs	114,248	114,248	114,248
R^2	0.005	0.038	0.155

Table VI

Size and Liquidity: 2SLS Regression Results for BHR_{m6}

This table reports the results of 2SLS regression analyses for six-month buy-and-hold returns (BHR_{m6}s) of two size groups and two liquidity groups. Small represents the firms in the first market capitalization quintile and Large represents the firms in the fifth quintile where quintiles are based on the NYSE cutoffs. Low liquidity firms are the firms in the fifth quintile and High represents the firms in the first quintile of the bid-ask spread measure. In the two-stage least squares (2SLS) approach, NPR and NPR × $SCFNQ_4$ are assumed to be endogenous and Fama-French 48 industry median values of those are used as instrumental variables in this approach. Here, $SCFNQ_4$ is a dummy variable indicating the highest SCFN quartile. Detailed definitions of other variables are available in Appendix A. The coefficient estimates are reported on top and *t*-statistics are reported in parentheses. In calculating *t*-statistics, clustered standard errors at the firm level are used. ***, **, * indicate that reported coefficient estimates are significantly different from zero at the one, five and 10 percent significance levels, respectively.

	Size		Liquidity	
	Small	Large	Low	High
NPR	7.97***	3.51***	4.46***	7.07***
	(7.84)	(3.32)	(4.81)	(7.21)
$SCFNQ_4$	-1.54*	1.00	-3.13***	-2.44**
	(-1.73)	(0.61)	(-2.59)	(-2.01)
NPR × $SCFNQ_4$	-3.72**	1.50	-5.05***	-2.85
	(-2.01)	(0.73)	(-2.90)	(-1.53)
ln(Size)	-10.90***	-8.83***	-8.68***	-9.37***
	(-10.52)	(-9.60)	(-10.66)	(-10.43)
BM	-2.45*	-2.76*	-0.98	-4.69***
	(-1.66)	(-1.96)	(-0.57)	(-2.65)
PARy1	-0.07***	-0.05***	-0.03***	-0.06***
	(-8.85)	(-4.82)	(-3.09)	(-5.03)
Profit	1.95	-1.29	2.73	-8.41**
	(0.38)	(-0.35)	(0.68)	(-2.00)
Investment	1.00	-1.34	1.99	-5.59***
	(0.52)	(-0.99)	(1.08)	(-2.95)
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
# of obs	29,725	36,641	10,753	10,627
R^2	0.23	0.20	0.22	0.22

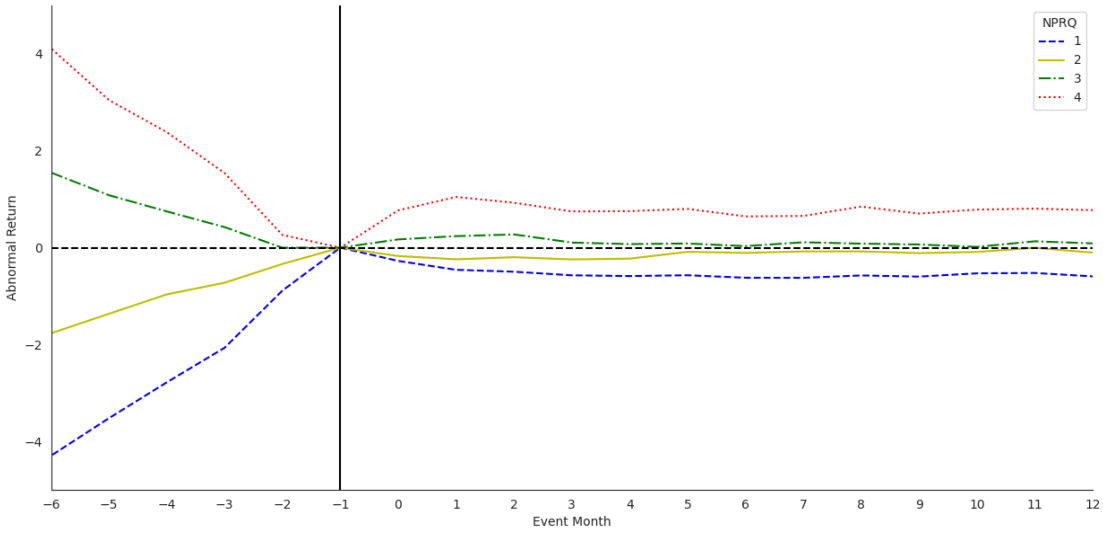
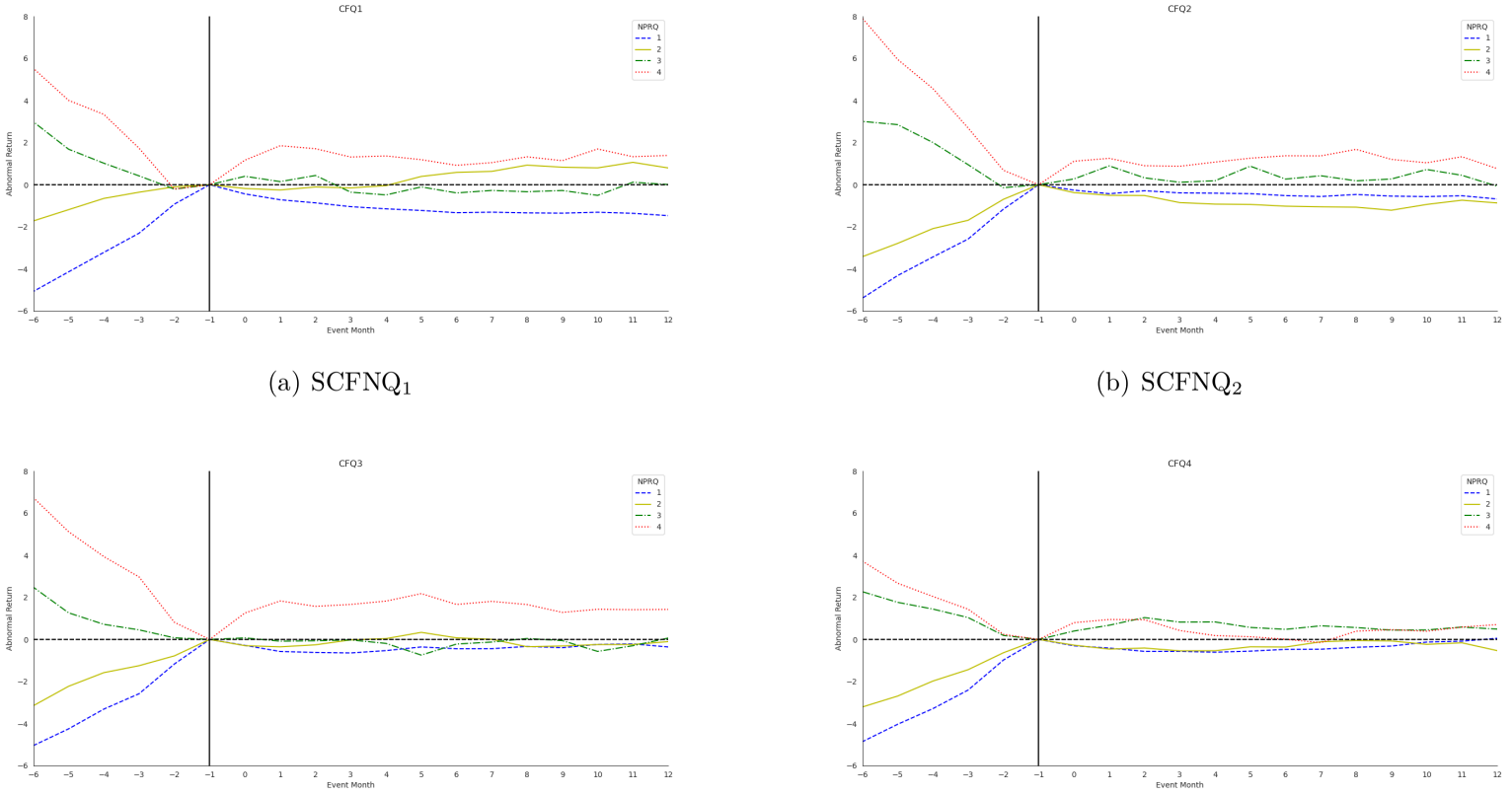


Figure 1. Monthly cumulative equally-weighted average abnormal returns around the formation of NPR quartiles. Figure 1 shows the cumulative equally-weighted average size, BM and momentum-adjusted monthly abnormal returns (CEWAAR) from six months prior to and twelve months following the NPR quartile formation (event month zero). The CEWAARs are set to be zero at the event month -1 by subtracting the CEWAAR value at the event month -1 ($CEWAAR_{-1}$) from all CEWAAR values. Monthly CEWAARs are calculated by cumulating (1+ equally-weighted average abnormal returns of all in each category) before subtracting $CEWAAR_{-1}$. NPR is defined as the number of buy transactions minus the number of sell transactions over the total number of buy and sell transactions during the prior six-month period ending at the end of each month with at least three insider transactions made by top managers during the six-month period. NPR quartiles are formed using absolute cutoff values of -0.95, 0 and 0.95.



(a) SCFNQ_1 (b) SCFNQ_2

(c) SCFNQ_3 (d) SCFNQ_4

Figure 2. Monthly cumulative equally-weighted average abnormal returns of NPRQs around the formation of NPRQs for each SCFNQ. Figure 2 shows the cumulative equally-weighted average size, BM and momentum-adjusted monthly abnormal returns (CEWAAR) from six months prior to and 12 months following the NPR quartile formation (event month zero) for each SCFNQ. The CEWAARs are set to be zero at the event month -1 by subtracting the CEWAAR value at the event month -1 (CEWAAR_{-1}) from all CEWAAR values. Monthly CEWAARs are calculated by cumulating (1+ equally-weighted average abnormal returns of all in each category) before subtracting CEWAAR_{-1}. NPR is defined as the number of buy transactions minus the number of sell transactions over the total number of buy and sell transactions during the prior six-month period ending at the end of each month with at least three insider transactions made by top managers during the six-month period. NPR quartiles are formed using absolute cutoff values of -0.95, 0 and 0.95. SCFNQ represents SCFN quartiles, where SCFN captures how sensitive individual firm's cash flow news (CFN) is to industry average CFNs.