Striking Up With the In Crowd: When Option Markets and Insiders Agree

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Abstract

We study whether the trading behavior of corporate insiders provides additional information to the market, after controlling for the public information integrated by sophisticated investors. First, we establish that insiders and option market participants trade in the same direction on average. Second, we show that insider trading is relatively more informed when the option market sentiment is positive. The marginal information content of insider trades is higher for firms with higher levels of information asymmetry and during time periods when future economic conditions are less certain.
1 Introduction

Corporate insiders have access to private information that may be informative about the true value of their firms. Due to this informational advantage, both the Securities and Exchange Commission (SEC) and firms attempt to curb corporate insiders’ use of private information when trading in their firms’ stock. Despite the threat of criminal prosecution, civil penalties (Garfinkel, 1997), and firm imposed trading blackouts (Bettis et al., 2000), the academic research suggests that the trades of corporate insiders can be informative about future equity returns (Jaffe, 1974; Seyhun, 1986; Lin and Howe, 1990; Rozeff and Zaman, 1988; Lakonishok and Lee, 2001).

Decoding the information content of insider trades can be a complex task, as many insider trades are motivated by the insider’s liquidity or diversification needs, and not private information (Cohen et al., 2012; Alldredge and Cicero, 2015; Cline et al., 2017). Insiders may also misjudge the pricing implications of their private information, especially when market participants include attentive, sophisticated investors. Even if the insiders trade on private information, the marginal value of that information may be insignificant relative to the public information that has been incorporated through the trading activity of sophisticated investors. In this paper, we argue that the informational value of insider trading varies depending on the public information incorporated by the markets. In other words: *Do insiders provide additional information to the market after controlling for public information incorporated by sophisticated investors?* Specifically, we use option market sentiment to parse the information content of insider trades. Through this lens, we examine the pricing implications, information environments, and fundamental outcomes of firms.

We turn to options markets as our source of publicly available sophisticated investors’ sentiment. Economists have traditionally recognized that the derivatives markets provide a suitable environment for sophisticated investors to exploit their informational advantage.
The option markets can help mask informed trades (Back, 1993; Easley et al., 1998), provide higher leverage (Black, 1975), and alleviate short-sale constraints (Ofek et al., 2004). Therefore, it is not surprising that traders in options markets tend to systematically predict earnings surprises (Roll et al., 2010; Jin et al., 2012), unscheduled client and product announcements (Jin et al., 2012), takeover announcements (Cao et al., 2005), events that trigger a significant market reaction (Jin et al., 2012), and future realized volatility (Ni et al., 2008). Collectively, these findings suggest that options traders are sophisticated investors that price both public and private information.1 Thus, our key insight is that the information available through the option markets is comprehensive and we can use it to decode the information content of the corporate insiders’ trading.

Our main tests examine the return predictability of monthly net insider trading activity conditional on options market sentiment. We employ the implied volatility spread (VS), which captures the deviations from put-call parity, as our main measure of sophisticated investor sentiment. This measure has been documented to provide information about the direction of future returns on underlying securities (Cremers and Weinbaum, 2010; Campbell et al., 2018).2 We capture insider sentiment at the firm-month level using the net buy ratio (NBR) of all insider trades. This measure has been linked to future performance in prior literature (Lakonishok and Lee, 2001; Cohen et al., 2012).

Our results can be summarized in these three key findings:

1. **Contemporaneous Trading Patterns.** First, we document that the option market sentiment is positively related to the net insider sentiment. We find that higher levels of the implied volatility spread are associated with higher levels of net insider buying.

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1In addition to truly private information, private signals should also include proprietary ways of interpreting existing public information. This interpretation is in line with the superior ability hypothesis of Kim and Verrecchia (1994).

2Even though the parity is based on the arbitrage-free condition, it is difficult to take advantage of these deviations directly. As a robustness check, we incorporated additional measures of informed trading from the option markets such as the option-to-stock trading imbalance and document qualitatively similar findings. We thank an anonymous referee for suggesting this test.
That is, option markets are bullish when insiders are bullish and bearish when insiders are bearish, on average. We show that this relationship is particularly pronounced in firms where information asymmetry is likely to be higher such as small and illiquid companies. Using option market trader classification data from NASDAQ ISE (International Securities Exchange), we also show that this relationship is not an artifact of model-based pricing, but actually reflects the net order imbalance in the call and put option markets. In firm-months where option markets and insiders’ sentiment are both positive, market makers must write over six percent of monthly call option volume in order to make the market. Likewise, when option market and insiders’ sentiment is negative we find that market makers must write over four percent of put option volume and buy about one percent of call option volume for the month.

2. *Incremental Value of Insider Information.* Second, we document that net insider demand is positively related to future returns. However, when we control for the sentiment of sophisticated traders, we show significant variation in the return predictability of insider information. When we consider insider trading activity conditional on the prevailing option market sentiment, the predictability of insider trading patterns declines as the option market sentiment becomes negative. In particular, we construct long-short portfolios based on net insider demand across option sentiment terciles and find that the marginal information of insider trades is most valuable when option market sentiment is positive; it is somewhat valuable when option market sentiment is neutral; and it does not appear to be valuable when option market sentiment is negative. The results of these tests are also robust to factor model specifications and Fama and MacBeth (1973) cross-sectional analysis. These results hold using the model-free option-to-stock volume ratio (Roll et al., 2010) as a proxy for option market sentiment. We also show that these results are not driven by the contemporaneous option market reaction to insider trading by repeating our analysis with lagged option market
sentiment.

3. **Information Environment.** Third, we investigate potential economic mechanisms that generate predictability associated with corporate insider trading. For this purpose, we consider the information environment of the firms in our sample. We first show that the return predictability of insider trades is more pronounced during recessions rather than expansions, suggesting that the information gap between insiders and the public widens during periods of uncertainty characteristic of economic contractions.\(^3\) We next split the sample into subgroups based on different firms’ characteristics including size, book-to-market, historical performance, volatility, and liquidity and examine return predictability within each subgroup. We document that the information content of insider trading has more return predictability among stocks with high information asymmetry. In particular, we find that predictability is more pronounced among small losers with high volatility and low liquidity. Also, we find that the predictability is consistently higher for insider buys when the public sentiment is positive. This result provides additional evidence that corporate insider trading contributes to market efficiency. Motivated by this finding, we examine the informational content of insider trading by investigating whether corporate insider trading is driven by fundamentals. We find that insiders are contrarian investors. We document that insiders are more likely to buy stocks that showed weak fundamental performance in the past and sell stocks that showed strong performance.

We document that our findings are most prominent among small firms as well as firms with high informational asymmetry and low liquidity. These securities are particularly sensitive to the *noisy price* bias which arises when observed prices do not always reflect the

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\(^3\)A Financial Times article dated April 9, 2020, shows that U.S. executives bought shares of their own firms in record numbers in March. This record surge in purchases comes amidst high levels of uncertainty surrounding the fate of many firms during the COVID-19 pandemic. The article is available at [https://www.ft.com/content/8c76c07f-0ee1-40d6-ad32-652c85646167](https://www.ft.com/content/8c76c07f-0ee1-40d6-ad32-652c85646167).
fundamental value of the security due to non-informational pricing components of bid-ask spreads such as inventory and processing costs, order imbalances, limits to arbitrage and others. Therefore, we have to confirm that our results stem from the informativeness of insider trades rather than the noisy price bias. In fact, when we use value-weighted portfolios to correct for the noisy prices, our results become weaker. Asparouhova et al. (2013) note that value weighting is not the only method of efficiently addressing the bias. In particular, they show that using prior returns to assign the weights to stocks in a portfolio also minimizes the bias; however, the advantage of return weighting is that it does not overweight large capitalization firms. This is especially important in our study since return predictability tends to concentrate among small firms.

The return-weighted results show that our findings persist after correcting for the noisy price bias. In other words, it is the informativeness of insider trades that drives the results and not the bias associated with the noisy prices of small stocks. Additionally, we show that our results hold even after eliminating firms with wide bid-ask spreads. Finally, we document that commonly accepted liquidity factors (Pástor and Stambaugh, 2003; Sadka, 2006) do not affect the abnormal performance of the hedge insider trading portfolio. Overall, our tests reasonably rule out the possibility that the findings presented in this paper are driven by the choice of the portfolio weighting scheme or lack of liquidity.

Our paper makes a number of important contributions to the literature. First, our results shed light on insider trading patterns, the information contained in insider demand, and how this information is incorporated into the option and equity markets (Penman, 1985, 1982). While Lakonishok and Lee (2001) document that insider buys are more likely to contain information, Gosnell et al. (1992) and Seyhun (1992) present evidence that insiders sell their holdings before bankruptcies. In this paper, instead of studying informed subsamples related to corporate events, we examine a systematic information component and focus on the total insider demand and its role in predicting future performance. We show that
insider trading is more informed when the option market sentiment is positive. Moreover, this relation is primarily driven by insider purchases and more pronounced among small and illiquid companies, which are more likely to be mispriced due to their poor information environment. Consistent with the prior literature, insider sales on average do not contain information even if option traders move in the same direction.

Second, we contribute to the option market literature by investigating the importance of the information content of the option-based sentiment. In particular, Biais and Hillion (1994) suggest that the introduction of the options reduces the probability of the market breakdown, which is beneficial to liquidity traders but may reduce insider profits. Similarly, Hyland et al. (2003) report lower insider trading activity for optioned stocks. Chakravarty et al. (2004) present evidence that option markets contribute to price discovery. Kacperczyk and Pagnotta (2018) study a broad set of informational signals conditional on unequivocally nonpublic insider trading. Our study provides additional evidence of the veracity of option market sentiment.

2 Data and Measures

Our primary sample is a monthly panel of all firms with exchange-traded options data available from OptionMetrics. The panel spans from January 1996 to December 2017. January 1996 is our start date as this is the first month of observations in the OptionMetrics data. The daily options market and insider trading data of each firm are aggregated to measures at month \( t \).\footnote{While current single option equity contracts traded on CBOE and NASDAQ specify a 16:00 EST trading close, historically the options markets have closed at 16:02 EST (Xing et al., 2010) and prior to 1998 16:10 EST Cremers and Weinbaum (2010). This allows the opportunity for material information released after 16:00 to be priced in the options markets but not the underlying equity market until the subsequent open. In order to deal with the asynchronous trading that could impact our portfolio formation, we follow prior literature and remove the final trading day observation of each month in our option measures calculations. Our results are materially similar if the final day of trading is included.} Insider trading data are from Thompson, return data are from CRSP, and
financial data are from Compustat. Data from CRSP only include observations for common equity (share code 10, 11, 12) with shares listed on NYSE/AMEX/NASDAQ (exchange code 1, 2, 3). We adjust for the delisting bias following Shumway (1997). Our final panel consists of 525,144 monthly observations.

The majority of our analysis concerns the short and long-horizon returns of firms conditional on the joint distribution of options market trading and insider trading, thus our two primary outcome measures are the characteristically-adjusted returns of Daniel et al. (1997) for portfolio sorting analysis, and excess returns for our factor model and Fama and MacBeth (1973) analysis. We calculate both types of returns over the subsequent month \((t + 1)\), quarter \((t + 1, t + 3)\), and semi-annum \((t + 1, t + 6)\). Our set of control variables include: month-end market capitalization, book equity to market equity measured at the most recent fiscal year-end, average daily illiquidity (Amihud, 2002) in month \(t\), realized monthly volatility of daily returns, and idiosyncratic volatility and idiosyncratic skewness calculated from the Fama and French (1993) three-factor model using daily returns within a month \(t\). A detailed description of all of the variables in our analysis can be found in Appendix Table A.

### 2.1 Measures of Option Market and Insider Trading Activity

**Volatility Spread**

Our main measure of option market sentiment is the volatility spread which represents the average difference in implied volatilities between the call and put options across option pairs matched on the strike price and maturity. High volatility spreads indicate that call options are more expensive relative to put options, suggesting positive sentiment in the options market, whereas low volatility spreads suggest negative sentiment. In constructing our volatility spread we follow Cremers and Weinbaum (2010), whose measure is also related
to the four volatility spread measures discussed in Amin et al. (2004). Specifically, for every
day $t$ and every stock $i$ with call and put option data on the day $t$, we compute the volatility
spread (VS) as

$$V S_{i,t} = IV_{i,t}^{\text{calls}} - IV_{i,t}^{\text{puts}} = \sum_{j=1}^{N_{i,t}} w_{j,t}^i (IV_{j,t}^{i,\text{call}} - IV_{j,t}^{i,\text{put}}) ,$$

(1)

where $j$ is the index of call and put option pairs matched on strikes and maturities, $N_{i,t}$ is
the number of valid option pairs on stock $i$ on day $t$, $w_{j,t}^i$ are the weights, and $IV_{i,j,t}$ are
the implied volatilities$^5$ from the option price file provided by OptionMetrics. We use open
interest in the call and put options as weights and therefore require that all option pairs used
in the VS calculation have positive open interest and valid (i.e., positive) implied volatilities.

**Option-to-Stock Volume**

As an alternative to the model-based VS measure of the option market sentiment, we estimate
the ratio of option-to-stock (O/S) trading volume. Roll et al. (2010) and Johnson and So
(2012) show that the O/S measure is inversely related to future returns and fundamental
information. We approximate daily option trading volume by aggregating the number of
contracts traded in the stock $i$’s options across all strikes, maturities, and types and adjusting
it upward by a factor of 100 to make it directly comparable with stock volume. We then
multiply it by the corresponding end-of-day midpoint price to estimate the dollar trading
volume. To arrive at a monthly measure, we add up the daily option dollar volume within
the month, omitting the last daily observation in each month. We follow a similar procedure
to estimate the equity dollar trading volume. The O/S ratio is calculated as:

$$O/S_{i,t} = \frac{O_{i,t}}{S_{i,t}} ,$$

(2)

$^5$OptionMetrics calculates implied volatilities using the Cox et al. (1979) binomial tree model.
where $O_{i,t}$ and $S_{i,t}$ are the approximate option and equity dollar volumes for firm $i$ on day $t$.

**Option Market Order Imbalance**

For a subset of our sample, we are able to measure the option market order imbalance using the NASDAQ ISE (International Securities Exchange) Open/Close trade profile provided by NASDAQ. The data contains the aggregate volume of opening and closing transactions by end-users and classifies end-users into three classes: Customer (a retail trader trades through a broker), Professional Customer (a member like Morgan Stanley or Goldman trades on behalf of a large customer), and Firm (a member enters a trade for their own account).\footnote{Firm trades can be sub-classified into Proprietary (executed on behalf of their own trading account) and Broker/Dealer trades (executed for a Broker/Dealer who is not a member of the exchange). It is possible that the Broker/Dealer trades also contain non-informative trades, as these institutions can trade to maintain or hedge their security inventory. In untabulated tests, we find that our results are similar if we omit Broker/Dealer trades from our main measure.} This data is available on a daily basis beginning in May 2005.

To measure net order imbalance (order flow absorbed by the market maker) we calculate the signed call and put ratios following Christoffersen et al. (2018). The signed call ratio is calculated as follows:

$$
\text{Signed Call Ratio}_{i,t} = \frac{\sum OpenBuy_{i,t}^{calls} + CloseBuy_{i,t}^{calls} - OpenSell_{i,t}^{calls} - CloseSell_{i,t}^{calls}}{\sum OpenBuy_{i,t}^{calls} + CloseBuy_{i,t}^{calls} + OpenSell_{i,t}^{calls} + CloseSell_{i,t}^{calls}},
$$

where we take the difference between the opening and closing buy and opening and closing sell trades of all end-users and scale by the total volume of all end-users across all available strikes and maturities for a firm $i$ at time $t$. We follow the same procedure above for the put option volume to calculate the signed put ratio. Finally, we calculate the net imbalance for the total option volume as the difference between the signed call and signed put ratios. Due to the zero-sum nature of options markets, positive values of the call (put) ratio indicate a bullish (bearish) market where excess call (put) buying by end-users must be met by market...
maker call (put) writing, and negative values of the call (put) ratio indicate a bearish (bullish) market where excess call (put) writing by end-users must be met by market maker call (put) buying. We find that the distributions of the signed option imbalance measures are similar to the values reported in Christoffersen et al. (2018).

**Net Insider Demand**

Insider trading data are obtained from the SEC Form 4 transactions from Thompson Reuters Insider Filings dataset. Our sample consists of all open market, direct and indirect ownership transactions of more than 100 shares of common stock.\(^7\) Our sample includes transactions both related to and unrelated to the exercise of executive stock options. We exclude observations that are amended to avoid double counting of transactions. The Form 4 filings are known to contain material errors where the transaction price or shares traded differ significantly from the CRSP price and shares outstanding. Following Lakonishok and Lee (2001), we delete observations where the transaction price differs from the CRSP close price on the transaction date by more than twenty percent in either direction. We also eliminate transactions where the transaction share amount is greater than twenty percent of CRSP shares outstanding on the transaction date. We create our main insider trading variable, net buy ratio (NBR), as follows:

\[
NBR_{i,t} = \frac{\text{Purchases}_{i,t} - \text{Sales}_{i,t}}{\text{Shrout}_{i,t}},
\]

where \(\text{Purchases}_{i,t}\) is the total number of shares purchased by the insiders of firm \(i\) in a month \(t\), \(\text{Sales}_{i,t}\) is the total number of shares sold by the insiders of firm \(i\) in a month \(t\), and \(\text{Shrout}_{i,t}\) is the total number of shares outstanding of firm \(i\) at the end of the month \(t\). This measure captures the net direction and magnitude of insider trades of a firm during a given month.

\(^7\)We follow Cohen et al. (2012) and keep observations with the following cleanse codes: R, H, L, I, C.
2.2 Summary Statistics

We present the summary statistics and distribution of the variables in our sample in Table I. The two main dependent variables of interest in our analysis are the volatility spread (VS) and the net buy ratio (NBR). The distribution of VS is -0.81 (-.68) at the mean (median) and becomes positive between 50th and 75th percentiles. This means that the put options are relatively more expensive on average, which is similar to the VS distribution in Cremers and Weinbaum (2010). NBR is zero in the inner quartile range, indicating that over half of trading months in our sample have no insider trades. This distribution of NBR is similar to that in Purnanandam and Seyhun (2018). We address this peculiar distribution in our analysis similar to Purnanandam and Seyhun (2018) by breaking NBR into distinct groups of insider “BUY” months where NBR is positive, insider “SELL” months where NBR is negative, and “NEUTRAL” months where insiders do not trade.

Table I also reports the distribution of the book-to-market ratio calculated at the most recent fiscal year-end (BM), ratio of monthly call to total option dollar volume (CODV), ratio of monthly average of mid-point scaled call and put bid-offer spreads (CPBO), ratio of monthly call to put open interest (CPOI), ratio of monthly call to put volume (CPVOL), monthly average 30-day 0.5-delta point on the call implied volatility surface (CVOL), monthly average equity bid-offer spread scaled by closing price (EBA), monthly equity dollar volume (EDV), monthly average Amihud (2002) illiquidity measure, idiosyncratic volatility (IVOL) and skewness (ISKW) calculated from the residuals of the Fama-French three-factor model estimated using daily returns during the month, market capitalization (MCAP), monthly option dollar volume (ODV), monthly average 30-day 0.5-delta point on the put implied volatility surface (PVOL), raw monthly return (RET), and realized volatility of daily returns during the month (RVOL) and signed call and put volumes.

[Insert Table I about here.]
The average value of NBR is negative (−0.01), which suggests that the majority of the insiders’ transactions are sales rather than buys. While this is indeed the case, we show that there are actually a substantial amount of firm-months observations in our sample where insiders are net buyers of their own firm’s stock. We plot the total number of firm-months by year where insiders are net buyers (NBR greater than zero) and net sellers (NBR less than zero) in Figure 1. We then repeat this analysis and plot the same information conditional on option market sentiment in Figure 2.

Figure 1 shows that insiders are indeed net sellers of the stock of their own companies. However, there is a substantial number of net buy months as well. This is especially pronounced around the years 2000 and 2008, which correspond to the Dot-Com Bubble and the Great Recession. The average number of net buy (net sale) firm-months in our sample per year is 1398 (6125). Similarly, we document that the lowest number of buys (sales) is 908 (4070).

Next, we consider the net buy and net sell firm-month distributions conditional on the option market sentiment. Figure 1 presents the prior analysis conditional on option markets being negative (low VS tercile), neutral (middle VS tercile), and positive (high VS tercile). The average number of net buy (net sell) firm-months per year for each case is 467 (1880), 410 (2452), 519 (1793), respectively. In sum, we find that while selling comprises a large fraction of insider trading, there is still a substantial amount of buying, especially around economic downturns.

While our data ends in 2017, in March 2020 The Financial Times reports that in the midst of the COVID-19 crisis over 994 firm insiders purchased $1.1 billion of their own stock. This is the largest dollar amount purchased in a month since October 2013, and the largest number of executives participating in purchases in a month since 1990.

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3 Empirical Results

We begin our analysis by investigating the relationship between insider trading patterns and option market activity. To this end, we test whether insiders and option markets tend to generate congruent trading signals on average. We then zero in on the directional (signed) call and put trading volume available from the NASDAQ ISE trade profile to determine whether option markets generate increased demand for call (put) options when insiders are net buyers (sellers). Finally, to document predictability of net insider demand in the context of option market sentiment we employ three empirical methods based on portfolio analysis: conditional double sorts with characteristically-adjusted returns, factor model regressions, and Fama and MacBeth (1973) regressions with portfolio indicators.

3.1 Trading Patterns of Insiders and Options Market Participants

Relationship Between Insider Trades and Option Market Sentiment

Our goal is to understand whether insiders and option market participants have a tendency to trade in a similar direction at a given point in time. We investigate this by regressing our measure of net insider demand (NBR) on the measure of the demand pressure in the option markets - the volatility spread (VS). To separate the effects of aggregate market-wide changes in the insider demand and ensure that time-invariant unobserved firm characteristics do not drive our results, we include the year and firm fixed effects in our models. To improve readability, we scaled the NBR measure by a factor of 100 for this test. We present the results of this analysis in Table II.

[Insert Table II about here.]

Column 1 reports coefficients from the regression based on the entire sample and shows that higher levels of the volatility spread are positively associated with higher net insider
buying. Over our full sample, a one percentage point increase in VS is associated with a 59 basis point increase in scaled net insider demand. In other words, insiders are buying when the option market sentiment is positive. To gain further insight into this relationship, we estimate the regressions separately for the sub-samples of firms based on common characteristics and test the difference in coefficients between relevant model pairs. Specifically, we test the difference between the VS coefficients in each model pair and report the corresponding \( \chi^2 \)-statistic at the bottom of the table.

First, we split firms each month into the large and small size groups based on the median of the market capitalization. Columns (2) and (3) report regressions coefficients for the small and large firm sub-samples, respectively. For the size split sample, the magnitude and significance of the VS coefficient is substantially higher among the small companies (0.69 vs. 0.01 with the \( \chi^2 \)-statistic of the difference equal to 6.83). One possibility is that small firms exhibit higher information asymmetry compared to large firms, creating an environment where insiders may have an informational advantage if they possess information not currently incorporated into prices through the option markets. Next, we examine how this relation varies among value and growth sub-samples. Columns (4) and (5) report regressions coefficients for these two groups, respectively. We assign firms to the value and growth categories using the median book-to-market ratio as the cut-off point and repeat the assignment each month. For both value and growth firms the estimated coefficients on VS are positive and significant at the 1% level. While the magnitude of the coefficient is higher in the growth firm sub-sample (0.64 vs. 0.52), the difference is not statistically significant. Columns (6) and (7) report regression coefficients based on prior return subsamples. We assign firms to the winner and loser categories using the median cumulative return over the previous six months as the cut-off point and repeat the assignment each month. For both winners and losers, the coefficients on VS are positive and significant at the 1%-level; however, the magnitude of the coefficient is higher in the winner firm sub-sample: 0.55 vs. 0.41.
Finally, we turn the sub-sample analysis based on idiosyncratic volatility (Columns 8 - 9) and liquidity (Columns 10 - 11). Both measures are likely to capture different aspects of asymmetric information. To create the liquidity sub-samples we use the median values of the Amihud (2002) illiquidity measure, and our idiosyncratic volatility measure is calculated using the residuals of the Fama and French (1993) three-factor model estimated using daily returns during the month. We find no significant difference between the VS coefficients in the idiosyncratic volatility subsamples. However, we do find that the positive relationship between VS and NBR is only positive and significant in the low liquidity subsample 0.64 (t-statistic = 7.78).

Overall, Table II presents the results suggesting that insiders and option market participants trade in the same direction on average. However, this relation is more pronounced among small and low liquidity firms, suggesting that the level of information asymmetry may play a role. Moreover, these types of stocks are particularly sensitive to the noisy price bias (Asparouhova et al., 2010, 2013). The observed price of these securities may contain noises coming from non-informational components of bid-ask spreads such as inventory and processing costs, non-synchronous trading, temporary order imbalances, limits to arbitrage, and other behavioral biases. A similar point has been raised in (Hou et al., 2018). The authors present evidence that the presence of micro-caps, which represent only 3% of the total market capitalization and account for the 60% number of stocks, may bias the portfolio returns because prices of these stocks exhibit higher levels of noise. Since we are interested in the fundamental value of the security, we have to be careful in our portfolio analysis and account for this issue.

A large proportion of insider trading activity remains unexplained by the option market sentiment. This motivates our future tests where we condition on option market sentiment and investigate performance implications of insider trading. The fact that the relation between VS and NBR varies across samples with different exposures to systematic risk factors
necessitates the use of risk-adjusted returns in our future tests.

**Common Trading of Insiders and Option Market Participants**

Because the option market signal (VS) is model-based and insider demand is a count of shares traded, we want to ensure that the actual option market trading activity is in the same direction as insider trading. As an alternative test, we use daily options trading data from the NASDAQ ISE with detailed trader classification. We construct the signed call ratio, signed put ratio, and the net imbalance ratio following Christoffersen et al. (2018). Positive values of the signed call (signed put) ratio indicate that there is excess end-user demand for buying calls (puts) that is fulfilled by market makers, and negative values of the signed call (signed put) ratio indicate excess writing of calls (puts) by end users that must be purchased by market makers. The net imbalance ratio is the difference between the signed call and signed put imbalance ratios. We discuss the construction of this measure and some data limitations in more detail in Section 2. For each month in our sample, we first sort firms into terciles based on option market sentiment measured by VS. Within each tercile of option market sentiment, we then bin firms into Insider Sell, Neutral, and Buy based on negative, zero, or positive values of NBR, respectively. Within each cell we report the average of the signed call ratio, signed put ratio, and net imbalance ratio. We report the results of this analysis in Table III. This test allows us to observe contemporaneous option market and insider trading activity while controlling for the current option market sentiment.

[Insert Table III about here.]

Panel A of Table III reports results based on our full sample. In the top two rows we report the mean and $t$-statistic of the signed call, signed put, and net imbalance ratios across our three insider trading categories without conditioning on option market sentiment. We find that in months when insiders are net sellers (buyers), the end users of options are writing
calls and buying puts (buying calls). When we consider the magnitudes of the results in the first two rows, they suggest that end users prefer to buy calls (puts) when insiders are net buyers (sellers) as opposed to writing puts (calls). For instance, when insiders are net sellers the market makers write 2.65% of put volume to meet end user demand, but they only write 0.13% of call option volume to meet end user demand. This univariate evidence suggests that options market end users and firm insiders trade in the same direction contemporaneously.

In the remainder of Panel A, we report the results of our bivariate sort of firms on VS and insider sentiment. Because VS is positively related to future returns, we label the rows Option Negative for the low VS tercile, Option Neutral for the middle VS tercile, and Option Positive for the high VS tercile. When insiders are selling and options sentiment is negative (positive) we find that option market end users are net writers (buyers) of calls and buyers (writers) of puts. When insiders are buying and options sentiment is positive (negative) we find that end users are buyers of calls and writers (buyers) of puts. We also note that when there is no insider trading during a month and the option sentiment from VS is positive (negative or neutral), we see significant net purchasing of calls (puts). While these results are expected based on our previous analysis, they do confirm that there is significant option market trading in the direction of insider sentiment and that insider information parsed through the lens of the prevailing option market sentiment is correlated with net end user trading.

Prior research suggests that some subsets of insider trades are more informative than others. One of the more prolific filters for insider trading data comes from Cohen et al. (2012), which classifies insider trades as “routine” and “non-routine”. The authors show that portfolios formed on non-routine insider trades can predict future returns. In Panel B of Table III we repeat our analysis of Panel A using monthly net buy ratios constructed only from the non-routine trades based on the filters proposed in Cohen et al. (2012). We find that the patterns of contemporaneous insider and option market trading activity are
similar when filtering out routine trades. Option market participants buy calls when insiders are buying and the VS indicates positive future returns, and buy puts and write calls when insiders are selling and the VS indicates negative future returns. Prior research also suggests that only the opening trades of option market end users are informative Pan and Poteshman (2006). To ensure that our results hold under this assumption, we reconstruct our imbalance measures using only opening purchase and sell trades in the spirit of the Pan and Poteshman (2006) information ratio. We report the results using this alternative measure in Panel C. In this Panel, we find that option market end users are buying significantly more calls and writing more puts when insiders are buying and options market sentiment is positive. However, when using this alternative measure, we do not find significant differences when option market sentiment is negative and insiders are selling.

3.2 Return Predictability of Insider Trades

*Portfolio Sorts With Characteristically-Adjusted Returns*

Our primary intent is to examine the predictive power of insider trading demand conditional on information contained in the trading patterns of options market participants. We begin with the unconditional (univariate) return predictability of three portfolios constructed based on the positive, zero, and negative insider net buying. Next, to test the incremental information content of insider trades, we perform conditional double sorts first on option market sentiment and then on insider trading patterns. The measure of future performance in our double sort analysis is the characteristically-adjusted return proposed in Daniel et al. (1997) (DGTW). For every month in our sample we first sort stocks into three terciles using VS, and then bin firms within each tercile based on NBR.

Asparouhova et al. (2013) show that portfolio analysis may be subject to bias and, in particular, the equal-weighted portfolio results may be overstated due to the prevalence of
noise attributable to market imperfections among small firms. While the authors point out that noise can arise from microstructure frictions such as bid-ask spreads, asynchronous trading, discrete price grids, and temporary price impacts of order imbalances, they also show that both value weighting (VW) and prior return weighting (RW) of stocks within portfolios address the noisy price bias and “the remaining bias in RW and VW estimates is minimal” (p. 706). Further, Asparouhova et al. (2013) argue that RW “provides a bias-corrected estimate that places equal weight on the information contained in each security” and VW “corrects for bias while weighting large firms more heavily”, so that the choice between the two methods may “depend on the desired weight to be given to the information contained in small versus large capitalization securities” (pp. 706-707).

Based on our evidence regarding the relationship between VS and NBR in Table II, we suspect that a large portion of any return predictability may be driven by smaller stocks with high idiosyncratic volatility and low liquidity. This would not be surprising given that insiders and option traders are more likely to be able to capitalize on their informational advantage in the stocks with arguably lower levels of publicly available information. We, therefore, expect to find weaker results in value-weighted portfolios, necessitating the use of return-weighted portfolio tests in order to correct for the noisy price bias without downplaying the information content of NBR and VS among small stocks. Panel A of Table IV presents the buy and hold, equal-weighted, DGTW-adjusted portfolio returns over the subsequent one, three, and six month periods. Panels B and C repeat this analysis using value-weighted and return-weighted portfolios, respectively.9

[Insert Table IV about here.]

First, we examine the unconditional performance of each insider trade bin. The first row in each panel of Table IV presents the future DGTW-adjusted performance of the INSIDER

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9As a robustness check we also use the NYSE decile weights and the adjusted market cap weights from Purnanandam and Seyhun (2018). We find that our results are materially similar to the equal-weighted and return-weighted results reported in Table IV.
SELL, INSIDER NEUTRAL, and INSIDER BUY bins. When insiders buy stocks of their own company, the future performance is positive and significant for equal-weighted and return-weighted portfolios, which is consistent with the notion that insiders buy when the company is relatively undervalued by the market. We document that the equal-weighted insider buy portfolio produces the abnormal performance of 38, 73, and 84 basis points over the next 1, 3, and 6 months after formation, respectively. Similarly, the return-weighted insider buy portfolio produces 32, 64, and 74 basis points of abnormal performance over the next 1, 3, and 6 months, respectively. Value-weighted portfolios show no return predictability of insider purchases at the 1- and 6-month horizons and only weak predictability at the 3-month horizon – 37 basis points with 10% significance. When insiders sell their firms’ stocks or do not trade at all, the future abnormal returns are not significantly different from zero in most cases. The only exceptions can be found in return-weighted portfolios at the 1-month horizon (−14 basis points with 10% significance) when insiders sell and at the 6-month horizon when insiders do not trade at all (−31 basis points with 5% significance).

When we form the hedge portfolio by taking a long position in the firms in the unconditional INSIDER BUY bin and a short position in the firms in the unconditional INSIDER SELL bin, we find that this trading strategy positively and significantly predicts abnormal returns over the 1, 3, and 6-month horizons when using equal-weighted and return-weighted portfolios but not when using value-weighted portfolios. Specifically, the hedge portfolio using equal weights (prior return weights) produces 49 (46), 86 (81), and 79 (76) basis points of abnormal performance over the next 1, 3, and 6 months, respectively. Overall, we find that insider trading unconditionally predicts future returns when using equal or prior return weights. However, the hedge portfolio performance is primarily driven by insider purchases and is not significant when we use the value weighting scheme.

Because insider purchases and not sales appear to drive the performance, it is of paramount importance to our research question to confirm that insider purchases remain strongly pre-
dictive of future returns even when the option market sentiment is positive, which motivates the rest of the analysis in Table IV. We examine the subsequent returns of insider trading portfolios within each stratum of option trading sentiment. The growing option markets present a rich environment for informed traders with the ability to process public information (Black, 1975; Back, 1993; Ofek et al., 2004). We use conditional sorts to control for the sentiment of sophisticated investors, which allows us to determine whether insider trades bring marginal information to the market. When option markets demonstrate a positive sentiment (OPTION POS), we observe that the performance of the insider trading strategy (long INSIDER BUY, short INSIDER SELL) is positive and significant when we use equal-weighted or return-weighted portfolios but not when we use value-weighted portfolios. Specifically, the insider hedge portfolio using equal weights (prior return weights) produces 70 (65), 142 (132), and 172 (172) basis points of abnormal performance over the next 1, 3, and 6-months, respectively. Moreover, in all cases insider purchases are driving the performance of the hedge portfolio: the long leg of the trading strategy generates equal-weighted (return-weighted) abnormal portfolio returns between 63 and 238 (49 and 219) basis points depending on the horizon. This suggests that the predictive ability of insider trading, and insider purchases in particular, remains significant even after accounting for the positive information coming from skilled investors trading on the public information in the option market.

When the option markets are neutral, we find that the performance of the insider trading strategy is still positive and significant but the overall magnitude and significance are lower. Specifically, the insider hedge portfolio using equal weights (prior return weights) produces 28 (29) and 57 (58) basis points of abnormal performance over the next 1 and 3 months, respectively. Noticeably, value-weighted portfolios also produce positive and significant abnormal performance – 42 and 61 basis points at the 1 and 3-month horizons. Our takeaway from these results is that although the sentiment of sophisticated traders’ is neutral, insider
trading carries information predictive of future returns.

Finally, we consider the case when the option markets demonstrate a negative sentiment. In this case, we show that while the INSIDER SELL portfolio generates negative and significant performance in the future when we use equal-weighted or return-weighted portfolios, the overall performance of the insider hedge portfolio is not significantly different from zero. For example, Panel A (Panel C) of Table IV shows that when options signal is negative the INSIDER SELL portfolio produces $-19 \ (-21)$ over the next month and $-39 \ (-40)$ basis points over the next 3 months. The performance of this portfolio reverses back to zero around the 6-month horizon. However, no return horizon or portfolio weighting scheme allows us to document any abnormal performance of the insider trading strategy (INSIDER HEDGE). This evidence supports the notion that insider trading is relatively less informative when option markets demonstrate a negative signal.

Our main inference from the conditional portfolio sorting confirms the informed status of corporate insiders' trades. That insider purchases remain predictive of future returns even in the presence of positive information impounded by the option market suggests additional information content of insider buying activity. In fact, the return predictability of insider trading is highest when option markets are bullish. One possibility is that the subset of actionable private information available to option market participants is strictly contained in the subset of actionable private information available to insiders and that insiders are able to exploit their informational advantage. This can happen when some but not all private information leaks to the wider public. Another possibility is that insiders are correct in interpreting available positive public information more optimistically than option market traders. This explanation is consistent with the idea that insiders may derive their informed status not only directly from new private information, but also indirectly through their private and more efficient means of interpreting public information.

Another key finding relates to the importance of the portfolio weighting scheme. By
overweighting large capitalization firms, value weighting all but eliminates the information content of insider trading in small stocks, which is likely to be more informed. Therefore, we follow the insight in Asparouhova et al. (2013) and use prior return weighting in subsequent tests as a way to address the noisy price bias without understating the information content of insider and option market trading in small stocks. Moreover, coupled with our previous finding that insiders and option market participants display common trading patterns precisely among small, less liquid stocks with high idiosyncratic volatility, our results motivate our future tests of the effects of liquidity and return predictability among these subsets of firms.

**Calendar-Time Regressions**

Next, we turn to calendar-time regressions to test whether commonly accepted asset pricing models can account for the return predictability of insider trading. We follow the previous sorting procedure and analyze the unconditional performance of the insider hedge portfolio (insider buys minus insider sells). We then control for the option market sentiment and repeat this analysis to examine the incremental information content of insider trades. Specifically, we regress the next month’s return of the insider hedge portfolio on the returns of factor-mimicking portfolios for the commonly accepted asset pricing factors. We use the comprehensive model advanced in Fama and French (2018), which incorporates six commonly accepted factors.\(^\text{10}\) The results of this analysis are reported in Table V. In this table, we report the average time-series loadings for the insider trading hedge portfolio unconditionally and also within each option market sentiment grouping.

\(^{10}\)As a robustness check as also use the standard Fama and French (1993) model, Carhart (1997) model, and Fama and French (2015) model. We document (untabulated) qualitatively similar results.
cant on average. Columns (1) and (2) show that the insider hedge portfolio produces 56 and 53 basis points using equal and return-weighted portfolios, respectively. This is consistent with the results document in Table IV. However, this analysis allows us to observe the sensitivity of the trading strategy to common asset-pricing factors. For example, we document negative and significant exposure to the momentum factor (UMD) but positive and significant loadings on the size (SMB), value (HML), and profitability (RMW). This suggests that insiders on average are buying small, value, losers with good profitability, which is consistent with the idea that insiders know information about their companies that markets do not have or able to incorporate efficiently.

When option market sentiment is positive, we find that the predictability of insider trades is strongest. According to Columns (7) and (8), the insider hedge portfolio generates 67 and 61 basis points per month using equal- and return-weighted averages, respectively. This analysis provides evidence that insiders contribute additional information to the market when the public sentiment is positive. Additional untabulated results reveal that in this case the performance of the hedge portfolio is mainly driven by the long leg of the trading strategy, i.e. by insider purchases. We also consider the cases where option traders are neutral or negative. Similar to the results observed in Table IV, we document weaker positive predictability when option markets are neutral and no predictability when option sentiment is negative. This is consistent with the notion the marginal information of insider trades decreases when sophisticated investor sentiment is neutral or negative.

To sum, we document that insider trading is informative and predicts future abnormal performance after accounting for common asset pricing factors. As in our conditional sorts with characteristically-adjusted returns, factor model regressions show that insider purchases are predictive of future returns even when option markets are positive; in fact, insider trading boasts its strongest return predictability in this case. Our main takeaway is that option markets cannot incorporate all positive (public or private) information into asset prices, leaving
insiders the opportunity to conduct profitable trades and contribute to market efficiency. Also, the loadings on the factor models suggest that the construction of the hedged portfolio is, in fact, feasible and not short-sale constrained. That is, the long side of the profitable hedged portfolio is composed of smaller firms which can be difficult to short, while the short side consists of larger firms which would be easier to short.\footnote{The factor loadings and alphas for the long and short legs of the strategy are available from the authors upon request.}

As we show above in Table II our findings are more pronounced among small and illiquid stocks and therefore sensitive to the choice of weight in the portfolio analysis. While we find that our findings are weaker when we use the value-weighted portfolios (untabulated), we argue that in our case the return-weighted adjustment is a more appropriate choice because the value weighting scheme corrects the noisy price bias by placing a larger weight on stocks with large market capitalization, where we do not expect to find a strong interaction between there trades of insiders and option market participants (see Table II). However, since our findings are sensitive to this issue, we have to confirm that the actual liquidity does not affect our results. To address liquidity concerns, we repeat our calendar-time regression analysis but this time we include priced liquidity factors as additional sources of systematic risk premiums. We start by adding the Pástor and Stambaugh (2003) factor to our benchmark regressions, which captures the noise in prices due to order flow. According to untabulated results,\footnote{To save space we do not report liquidity related analyses in the paper but they are available upon request.} the Pástor and Stambaugh (2003) factor does not load significantly on hedge insider portfolio across all models. In addition, the intercept remains positive (65 basis points equal-weighted, 59 basis points return-weighted) and strongly significant when option markets are positive; it is still positive (31 basis points equal-weighted and return-weighted) but weakly significant when option markets are neutral. When we instead use the liquidity factors suggested by Sadka (2006), we still document qualitatively similar findings (untabulated). Thus, we find that our results are not driven by the pricing components related to liquidity.
We also check if the actual liquidity or size effects play a role in our results. For example, Asparouhova et al. (2013) suggest that the bias may be substantially reduced by eliminating wide bid-ask spread securities. We follow their suggestion and eliminate stocks with the bid-ask spread above the median and repeat our main portfolio analyses. According to untabulated results, the overall inferences are still valid - insiders provide additional information about their own company but this is primarily driven by their buying activity when option markets are optimistic. Lastly, we show that our sample is comprised of relatively large firms. Untabulated results show that the average firm size in the portfolio containing smallest firms is $3.0 billion (when option traders are negative and insiders are neutral) and the average firm size in the portfolio containing largest firms is $14.5 billion (when both types are neutral).\textsuperscript{13} This is not surprising since only relatively large companies have option trading activity in the first place.

\textit{Fama-MacBeth Regressions}

As an alternative to portfolio sorting and calendar time factor-model portfolio regressions presented in Tables IV and V, we also employ the Fama and MacBeth (1973) approach by running cross-sectional regressions every month and then reporting the time-series average of the coefficients. The dependent variable is the buy-and-hold return of a stock over the next one, three, or six months, depending on specification. To parallel our results with portfolio sorts, we create a set of indicator variables based on the interactions of net insider demand and option market sentiment. We first sort stocks into three categories (OPTION NEG, OPTION NTRL, and OPTION POS) based on option market sentiment as measured by the volatility spread in month $t$. Within each option sentiment category, we then sort stocks into groups with negative net insider demand (INSIDER SELL), positive net demand (INSIDER BUY), and zero net demand (INSIDER NTRL) in month $t$. The interaction

\textsuperscript{13}For comparison, the $3.0 billion market capitalization is on par with the market capitalization of the Russel 1000 Index constituents ranked 900-1000 in terms of size.
terms are formed by intersecting the option market sentiment indicators with the net insider demand indicators, resulting in nine interaction term indicators. We omit the indicator variable OPTION NTRL × INSIDER NTRL because this is the benchmark portfolio where both signals are neutral. The coefficients on the interaction indicators in the regression represent the difference in the returns to a strategy that buys stocks with a given combination of option market sentiment and net insider demand as compared to a strategy that follows neutral signals from both insiders and option markets.

There are three advantages to using the Fama and MacBeth (1973) method. First, it makes it possible to confirm the robustness of our results to a characteristics-based adjustment for common risk factors (Daniel and Titman, 1997). Second, it allows us to include in the regression model other observable variables known to have predictive power for future returns. Third, by testing the equality of certain coefficients, we can readily compare the incremental predictive power of net insider demand conditional on the level of option market sentiment. Table VI presents the results of this analysis. The first three columns report the results based on ordinary least squares (equal-weighted) in each cross-section; the last three columns repeat the procedure using weighted least squares in each cross section. Following Asparouhova et al. (2013), we use the prior month’s gross return as the weight to minimize the noisy price bias.

Consistent with our previous results, stocks featuring positive option market sentiment and high net insider demand outperform the stocks in the baseline group by 58, 145, and 246 basis points over the next one, three, and six months based on the equal-weighted specification. For the return-weighted specification, this group of stocks demonstrates statistically significant outperformance of 93 basis points only at the six-month horizon. Overall, the performance of the group of stocks with positive option market sentiment and high net insider demand relative to the baseline groups is considerably weaker in the return-weighted specification compared to the equal-weighted specification. Since return weighting addresses
the noisy price bias without overweighting large capitalization firms (Asparouhova et al., 2013), we are inclined to conclude that some of the performance differential documented in the equal-weighted specification can indeed be attributed to the upward bias among small stocks.

Two other notable stock groups are those with zero or negative net insider demand and negative option market sentiment. Stocks in these groups consistently underperform stocks in the baseline group by between 21 and 185 basis points, depending on horizon and specification. Interestingly, return-weighted results in these stock groups are statistically significant and stronger than equal-weighted results in terms of the magnitude. There is no evidence that return weighting significantly undermines the return predictability associated with stocks with negative option market sentiment and zero/negative net insider demand. Ultimately, we would like to compare the performance of stocks with positive net insider demand and stocks with negative net insider demand before we make a final determination whether our results are driven by informed trading or by noisy prices.

[Insert Table VI about here.] At the bottom of the table, we present the statistical tests of the difference in coefficients indicating positive and negative net insider demand within each option market sentiment group. These tests mimic the performance of the hedge portfolios used in previous analyses and allow us to measure the incremental value of insider information. We find that the difference in returns between the INSIDER BUY and INSIDER SELL groups is positive and highly significant when option markets are positive and less significant when option markets are neutral or negative. Specifically, the performance difference in the equal-weighted specification ranges from 76 (one-month) to 170 (six-month) basis points, all significant at the 1% level, when option markets are positive. In the return-weighted specification, the

\[ \text{The test statistic has the } t\text{-distribution because the test compares the time-series of coefficients generated by the Fama and MacBeth (1973) procedure.} \]
performance differential is 72 basis points over the next month (significant at the 1% level) and 91 basis points (significant at the 5% level) over the next three months. When option markets are neutral, stocks in the INSIDER BUY group outperform stocks in the INSIDER SELL group by 32 basis points with 10% significance (60 basis points with 1% significance in the return-weighted specification) over the next month. Interestingly, even when option markets are negative the return-weighted specification indicates that stocks in the INSIDER BUY group outperform stocks in the INSIDER SELL group by 47 (100) basis points (significant at the 10% level) over the next month (next three months), whereas equal weighting produces no significant differences.

Overall, when option market sentiment is neutral or negative, we document that return weighting produces results that are on par with equal-weighted results. However, return weighting tends to produce weaker but still highly significant results at least over the next month when option market sentiment is positive. Nevertheless, we do not have sufficient evidence to conclude that our results are purely driven by the effect of noisy prices. Instead, the more plausible explanation is our hypothesis that insider trades are informative even after accounting for the public information impounded by option market participants.  

To ensure our Fama-Macbeth results in Table VI are robust to a variety of estimation techniques, we reestimate using pooled OLS and WLS methodology with the two-way firm and time clustered standard errors (Petersen, 2009; Gow et al., 2010). We also perform the same analysis using firm and year fixed effects. The results (untabulated) stay qualitatively similar. These results confirm our previous findings. First, insider trading contains incremental return-relevant information beyond what options markets generate. This is readily

15We confirm this conclusion with alternative weighting schemes. Using market capitalization weights (NYSE decile weights) we find that stocks in the INSIDER BUY group outperform stocks in the INSIDER SELL group by 89 (87), 148 (221), and 157 (203) basis points over the next one, three, and six months with 1% significance across the board, when option markets are positive. We also find that when option markets are neutral the market capitalization-weighted specification produces differential performance between the insider buy and sell groups equal to 61 basis points over the next month, significant at the 5% level.
apparent from return predictability on insider trades when option markets are uninformative (neutral). Even in the group of stocks with positive option market sentiment, those that receive a positive signal from insiders significantly outperform those that receive a negative signal. Second, insider purchases are a much stronger predictor of future returns than insider sales. One explanation for this finding is that insider purchases are more likely to reflect private information rather than sales since sales are often scheduled in advance as part of overall stock liquidation plans and are also more heavily scrutinized if they occur outside of such plans.

4 Additional Analyses and Robustness

In this section, we conduct additional analyses to establish the robustness of our main results and examine the sources of return predictability of insider trades. We begin by showing that our results are robust to conditioning on lagged option market sentiment. Then we show robustness to an alternative measure of option market sentiment based on the relative trading volume of options and equity. We conclude by examining the value of insider information in expansions versus recessions, return predictability in different subsamples based on firm characteristics, and the contrarian nature of insider trading.

4.1 Alternative Measures of Option Market Sentiment

Lagged Volatility Spread

In our baseline tests, we construct portfolios based on contemporaneous insider trading and option market signals. In particular, we construct month $t$ signals by averaging daily signals within the month and then track subsequent returns of portfolios formed on month $t$ signals. To examine the timing of option market activity relative to insider trading in more detail, we adopt an alternative sorting strategy. Our concern is that option traders observe insider
trades with a two day lag and make their trades accordingly. Because our measures of option market sentiment and insider trading are monthly aggregates, it is possible that our results are contaminated by the fact that option traders are simply mimicking insiders rather than acting on their own information. On the one hand, this mimicking is not necessarily undesirable as long as option traders only follow those insider trades that they believe to be value-relevant or informative. This is a part of the confirmation mechanism that we explore in our main analysis. On the other hand, if the option traders simply execute trading strategies based on all insider signals without incorporating their own beliefs, our results thus far do little to separate the marginal information content of insider trades from the sentiment reflected in option market activity. While we believe that it is not likely that sophisticated option traders blindly follow insider trades, we nonetheless provide an alternative test that uses option signals lagged by one month relative to the insider trading signals.\footnote{We thank an anonymous referee for suggesting this test as a way to address potential contamination of our option market signal.}

Table VII reports the results of this analysis. We first sort stocks into three categories (OPTION NEG, OPTION NTRL, and OPTION POS) based on option market sentiment as measured by the volatility spread in month $t-1$. Within each option sentiment category, we then sort stocks into groups with negative net insider demand (INSIDER SELL), positive net demand (INSIDER BUY), and zero net demand (INSIDER NTRL) in month $t$. We also repeat previously reported sorting based on net insider demand without conditioning on option market sentiment for comparison purposes. Panel A presents DGTW-adjusted returns of equal-weighted portfolios in months $t+1$, $(t+1, t+3)$, and $(t+1, t+6)$, while Panel B presents results for the return-weighted portfolios.

[Insert Table VII about here.]

Unconditionally, a portfolio that buys stocks with positive net insider demand and sells

\[16\]
stocks with negative net inside demand generates 49 basis points of abnormal performance (46 basis points for return-weighted portfolios) over the next month. When we condition on option market sentiment observed in month \( t - 1 \), the insider demand hedge portfolio generates abnormal returns of 71 basis points when option market sentiment is positive and 29 basis points when options market sentiment is neutral (71 and 27 basis points for return-weighted portfolios). There is no additional value in the insider demand hedge portfolio when options market information is negative. This pattern of abnormal returns continues for an additional two months and even beyond in the case of positive option market sentiment. Overall, these results are quantitatively similar to our main results presented in Table IV. Insider net demand is predictive of future returns, particularly insider purchases. The predictability is stronger when option market sentiment is positive in the preceding month. Importantly, insider trades continue to contain information about future returns even when option markets are neutral. These findings support our previous results regarding the marginal value of the information contained in insider trades.

**Option-to-Stock Volume Ratio**

So far we have focused on the volatility spread (Cremers and Weinbaum, 2010) as our measure of option market sentiment. This is a price-based measure that captures deviations from put-call parity that cannot be arbitrated away and therefore reveals return-relevant information generated in option markets. To capture this information, we now focus on the aggregate option market trading activity\(^{17}\) rather than the price imbalance between call and put options. Specifically, we use the option-to-stock dollar volume ratio (dollar O/S ratio) defined in Roll et al. (2010).\(^{18}\) Johnson and So (2012) show that the share O/S ratio predicts future returns at the one-week horizon, while Chichernea et al. (2020) show that the dollar O/S ratio predicts returns over the next quarter. The central idea in Johnson and

\(^{17}\)We thank an anonymous referee for suggesting a test using the option-to-stock volume ratio.

\(^{18}\)Please refer to equation (2) in section 2 for more details about the construction of the O/S measure.
So (2012) is that the ability of the O/S ratio to negatively predict returns arises from short-sale constraints that force informed traders to trade more frequently in the option markets when in possession of a negative signal than when in possession of a positive signal. When the dollar O/S ratio is high, option traders are more likely to possess a negative signal. We repeat our Fama and MacBeth (1973) analysis by first sorting stocks in month $t$ into the high dollar O/S group (OPTION NEG), low dollar O/S group (OPTION POS), and intermediate dollar O/S group (OPTION NTRL). Within each of these groups, we then sort stocks into three bins based on their net insider demand in month $t$ (INSIDER BUY, INSIDER SELL, and INSIDER NTRL). We include the indicator variables signifying belonging to one of the eight portfolios created by the sorting procedure (the base group OPTION NTRL × INSIDER NTRL is omitted) as explanatory variables in the regression using future returns as the dependent variable.

First three columns of Table VIII report results for future returns over the next one, three, and six months using ordinary least squares (equal-weighted) in each cross-section of the Fama and MacBeth (1973) procedure. The last three columns repeat the analysis using weighted least squares in each cross-section with the prior month’s gross return as the weight (Asparouhova et al., 2013) to minimize the effect on noisy prices on our inference. Consistent with our previous results, stocks receiving a positive signal from the option markets (low dollar O/S) and exhibiting positive net insider demand generate future one-, three-, and six-month returns of 37, 104, and 182 basis points (24, 106, and 175 basis points in the return-weighted specification). Importantly, positive net insider demand is predictive of future gains even when the option markets are neutral: stocks in the OPTION NTRL × INSIDER BUY portfolio generate future returns of 49, 108, and 144 basis points depending on the horizon (44, 97, and 43 basis points in the return-weighted specification.)
To focus on the incremental value of insider information, we calculate the differences in the coefficients on the indicator variables for positive and negative net insider demand within each option market sentiment group. The corresponding statistical tests are reported at the bottom of Table VIII.\textsuperscript{19} We find that the INSIDER SELL group significantly underperforms the INSIDER BUY group when option markets are positively inclined: the performance difference is highly statistically significant across all horizons using both the equal-weighted and return-weighted specifications. Even when option markets are neutral, the group of stocks with positive net insider demand outperforms the stocks with negative demand: the difference is statistically significant across all horizons for the equal-weighted specification and at the one-month horizon for the return-weighted specification. When the option market sentiment is negative, we do not observe a consistent pattern of return predictability associated with insider trading.

These results are consistent with our main findings that (1) insider trading generates additional return-relevant information beyond what is already expressed in the option markets; (2) return predictability is mainly driven by net insider purchases rather than sales. Interestingly, the predictive ability of insider trading in this section is stronger compared to our main results that use the volatility spread as the measure of option market sentiment. Our interpretation is that the dollar O/S ratio captures less return-relevant information expressed in the option markets than the volatility spread, leaving more information to be revealed by insider trading activity.

\textsuperscript{19}The test statistic has the \textit{t}-distribution because the test compares the time-series of coefficients generated by the Fama and MacBeth (1973) procedure.
4.2 Sources of Return Predictability of Insider Trades

*Value of Insider Information Over the Business Cycle*

When do insiders command an edge over sophisticated option market investors? It stands to reason that the size of the gap between public information processed by sophisticated investors and truly private signals received by corporate insiders likely depends on the overall economic uncertainty. In uncertain times, such as economic contractions, valuation models used by option traders likely produce a wider range of possible firm values and the resulting trades are less informative. At the same time, corporate insiders have an advantage in interpreting the financial position of their firms within the larger context of economic turmoil.

To determine whether the economic cycle affects the return predictability of insider trades conditional on option market sentiment, we repeat our factor model analysis and present the results in graphical form in Figure 3. We first sort stocks into three categories (OPTION NEG, OPTION NTRL, and OPTION POS) based on option market sentiment as measured by the volatility spread and then form the equal-weighted BUY (SELL) portfolios that take a long position in the stocks with positive (negative) net insider demand unconditionally and within each option market sentiment group. To determine abnormal performance of these portfolios, we regress next month’s excess return of each portfolio on the six asset pricing factors identified in *Fama and French (2018)*: the market excess return (MKTRF), the size factor (SMB), the value factor (HML), the momentum factor (UMD), the profitability factor (RMW), and the investment factor (CMA). In order to see the effect of the business cycle, we run these regressions separately for NBER recession and expansion months.

[Insert Figure 3 about here.]

In Figure 3, the points represent the alphas of each portfolio and the lines represent the two standard error confidence intervals. The figure clearly illustrates that the insider BUY portfolio is responsible for the predictability of insider trades. During expansions,
this portfolio produces positive abnormal performance of about 50 basis points per month; however, abnormal performance jumps to over 200 basis points per month during recession. When we condition on option market sentiment, we continue to observe return predictability of insider purchases, but only when option market sentiment is positive. More importantly, this predictability is primarily driven by the performance of the insider BUY portfolio during recessions - highly significant at over 400 basis points per month despite the wide confidence interval. These results support our intuition that as the information gap between insiders and sophisticated investors widens during periods of uncertainty characteristic of economic contractions, return predictability of insider trades becomes stronger.

Return Predictability and Firm Characteristics

Next, we consider the return predictability across various firm characteristics. To do this we employ the similar to that reported in Table VI. For each month in our sample, we split the sample at the median by market capitalization (SMALL/LARGE), market to book ratio (VALUE/GROWTH), prior six-month return (LOSERS/WINNERS), idiosyncratic volatility (HIGH IV/LOW IV), and liquidity (HIGH LIQ/LOW LIQ); consistent with our analysis in able II. We then regress next month’s excess return on the eight portfolio indicators and the controls reported in Table VI. The results of this analysis are reported in Table IX. For readability, we only report the statistics for the portfolio coefficients. Below each model, we also report the statistics for the difference between the specified portfolio coefficients.

[Insert Table IX about here.]

In the first two columns, we report the results for the size split samples. The coefficient estimates represent the equal-weighted excess return to each of the eight portfolios after controlling for additional risk factors. For the SMALL sample, we find significant predictability when insiders and option markets sentiment coincides (I,VII), however, this
return predictability does not survive in the LARGE sample. If we consider the marginal value of insider information under various option market conditions, we find that in the SMALL sample there is significant information contained in the net insider demand when option markets are bearish (III - I). When option markets are bearish the returns to the hedged portfolio formed by going long insider buy firms and short insider sales firms leads to return of 62 basis points per month. When options markets are bullish (VIII-VI) the return to the hedged portfolio is 105 basis points per month. However, these results do not hold for the LARGE sample. The individual portfolio returns are mostly insignificant, and likewise with the hedged portfolios. These results suggest that there is significant information in the trades of corporate insiders for smaller firms.

For the VALUE and GROWTH samples, we find that the marginal information of insider trades is significant across all option market conditions for the VALUE group, however, it is only significant for the GROWTH group when option market conditions are positive. For the LOSERS sample we find that the insider information is significant when the options market is bullish, but find no significance in the GROWTH sample. For the HIGH IV and LOW IV split, we find that the insider information is significant for the HIGH IV group when option markets are bullish, but insignificant otherwise. Finally, we find that the insider trades contains significant information for firms in the LOW LIQ group when option markets are both bullish and bearish. However, for firms within the HIGH LIQ group, we do not find marginal information in the insider trades. Taken together, these results suggest that insider information is valuable for firms that traditionally experience higher levels of informational asymmetry. This suggests that insider trades contribute to market efficiency, which is especially valuable for stocks with high informational asymmetry.
**Fundamental Information and Contrarian Behavior**

In our final test, we check whether insider trading is sensitive to the information related to earnings. Our goal is to determine whether, given a level of option market sentiment, insiders execute their trades in response to misvaluation that can occur when the market overreacts to previously reported fundamental information. To test this proposition we model the log odds of our INSIDER BUY and INSIDER SELL indicator variables as a function of different earnings measures reported prior to the initiation of the trades. In particular, we use standardized unexpected earnings (SUE) and an indicator variable that equals one if the company has met or exceeded its consensus earnings forecast (MEET). Table X reports the results.

[Insert Table X about here.]

In the first four columns, we restrict the sample only to those stocks that featured negative option market sentiment, whereas in the middle four and last four columns we use only the stocks with neutral and positive option market sentiment, respectively. Each column represents a logit regression of either INSIDER BUY or INSIDER SELL indicator on either SUE or MEET and a set of controls, including time and year fixed effects. Consistent with the contrarian nature of insider trades previously documented in Seyhun (1992), Rozeff and Zaman (1998), Lakonishok and Lee (2001), and Piotroski and Roulstone (2005), we find that meeting or exceeding the earnings forecast lowers the probability of observing positive net insider demand in subsequent months. Similarly, high standardized unexpected earnings tend to be followed by lower net insider demand. On the other hand, firms that come short of their earnings forecast are likely to experience increased insider buying in subsequent months.

The contrarian pattern on insider trading is observed across all option sentiment groups. We do observe slightly lower (higher) sensitivity of net insider purchases (sales) to positive
fundamental information in the positive option market sentiment group compared to other
groups, but the differences are not statistically significant. Overall, results in Table X in-
dicate that insiders act as contrarian investors and tend to buy stocks that showed weak
performance in the past and sell stocks that showed strong performance. Consistent with
the view of Kim and Verrecchia (1994), both insiders and option traders may possess private
ways of interpreting existing public information that allows them to identify stocks that
were underpriced following a weak earnings announcement and stocks that were overpriced
following a strong earnings announcement. As long as insiders are more likely to use other
private information for purchases and not sales, the concentration of insider trades’ return
predictability in the neutral and positive option sentiment groups is consistent with the in-
discriminate pattern of contrarian insider behavior presented here (even though contrarian,
insider trades do not bring any new information when option markets are negative).

5 Conclusion

We conjecture that while corporate insiders may have access to and trade on private infor-
mation, they are unlikely to possess the public information processing ability of sophisticated
investors. While insiders may believe that their private information would lead to returns in
a particular direction, the available public information processed by sophisticated investors
may outweigh the value of the insiders’ private information. In this paper we investigate the
marginal information of corporate insider trading in the context of sophisticated investor
sentiment.

Using measures of option market sentiment that have been shown to predict future re-
turns, we show that on average corporate insiders and option market participants generally
trade in the same direction. Similar other studies we show that insider return predictability
is generally concentrated in insider purchases. However, when we stratify firms by option
market sentiment, we show that insider purchases are strongly informative when option mar-
ket sentiment is positive, weakly informative when option market sentiment is neutral, and
not informative when option market sentiment is negative. Forming hedged portfolios based
first on sophisticated investor sentiment and then insider trades leads to significantly more
profitable portfolios formed on insider trades alone. Our results are robust to a number of
methodologies including calendar time factor models and cross-sectional regression analysis,
portfolio weighting schemes, and portfolio timing specifications.

We also propose that the marginal information contained in insider trading activity is
varying in both the cross-section and over time. In the cross section, we show that the
marginal predictive power of insider trades is higher for firms with higher levels of information
asymmetry. Over time, we find that the marginal preceptive power of insider trades is higher
when economic uncertainty is higher. Finally, we also show that insider trading behavior is
contrarian to firm fundamentals. That is, insiders sell more after good earnings news, and
purchase more after disappointing earnings news.
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Figure 1:
Unconditional Distribution of Net Insider Trade Months.

This figure presents the frequency of months in a given year where insiders are net buyers and net sellers of their firm’s stock. Frequencies above zero represent the number of firm-months in a year where insiders are net buyers. Frequencies below zero represent the number of firm-months where insiders are net sellers.
Figure 2:
Conditional Distribution of Net Insider Trade Months.

This figure presents the frequency of months in a given year where insiders are net buyers and net sellers of their firm’s stock for three cases of option market sentiment: negative (OPTION NEG), neutral (OPTION NTRL), and positive (OPTION POS). Option market sentiment is determined by dividing firm-months into terciles based on the volatility spread. Frequencies above zero represent the number of firm-months in a year where insiders are net buyers. Frequencies below zero represent the number of firm-months where insiders are net sellers.
This figure presents future abnormal performance (Fama and French (2018) six-factor alpha) of net insider demand portfolios during periods of economic expansions and contractions. Each month, we first sort firms into terciles based on VS. We label these OPTION NEG (bottom VS tercile), OPTION NTRL (middle VS tercile), and OPTION POS (top VS tercile). We form the BUY (SELL) portfolios that take a long position in the stocks with positive (negative) net insider demand unconditionally and within each option market sentiment group. We then obtain the alphas by regressing the next month’s return of each equal-weighted portfolio on the following risk factors: the market excess return factor (MKTRF), the size factor (SMB), the value factor (HML), the momentum factor (UMD), the profitability factor (RMW), and the investment factor (CMA). We run the regressions separately for NBER expansion and recession months. Points (circles, diamonds, triangles, and squares) represent the alphas and the lines represent the two standard error confidence intervals.
Table I: Summary Statistics.

This table presents summary statistics of our panel of 525,144 monthly observations spanning January 1996 to December 2017. Columns correspond to the mean, standard deviation, 10-th, 25-th, 50-th, 75-th, and 90-th percentiles of each variable. NBR is the net buy ratio of monthly insider transactions given by Equation 4. VS is the volatility spread between the calls and puts of a firm’s option chain given by Equation 1. BM is the book-to-market ratio calculated at the most recent fiscal year end. CODV is the ratio of monthly call to total option dollar volume. CPBO is the ratio of the monthly average of mid-point-scaled call and put bid-offer spreads. CPOI is the ratio of monthly call to put open interest. CPVOL is the ratio of monthly call to put volume. CVOL is the monthly average 30-day 0.5-delta point on the call implied volatility surface. EBA is the monthly average equity bid-offer spread scaled by the closing price. EDV is the monthly equity dollar volume. ILLQ is the monthly average Amihud (2002) illiquidity measure. ISKW and IVOL are the idiosyncratic skewness and volatility calculated from the residuals of the Fama-French three-factor model estimated using daily returns during the month. MCAP is the month-end market capitalization. ODV is the monthly option (call and put) dollar volume. PVOL is the monthly average of 30-day 0.5-delta point on the put implied volatility surface. RET is the raw monthly return. RVOL is the realized volatility of daily returns during the month. NBR, VS, CODV, CPBO, CPOI, CPVOL, CVOL, EBA, IVOL, PVOL, RET, RVOL, and signed ratios are all measured in percentage points. EDV, MCAP, and ODV are measured in millions of dollars. ILLQ is measured in basis points per one thousand dollars.

|       | Mean | Sd  | 10%  | 25%  | Median | 75%  | 90%  |
|-------|------|-----|------|------|--------|------|------|
| NBR   | -0.01| 0.05| -0.02| -0.00| 0.00   | 0.00 | 0.00 |
| VS    | -0.81| 8.09| -5.20| -2.27| -0.68  | 0.62 | 3.22 |
| BM    | 0.54 | 0.55| 0.14 | 0.24 | 0.42   | 0.68 | 1.01 |
| CODV  | 63.93| 25.19| 26.88| 47.17| 67.49  | 84.57| 94.78|
| CPBO  | 186.53| 384.04| 35.65| 60.02| 98.12  | 168.66| 336.02|
| CPOI  | 431.06| 2414.47| 69.90| 110.36| 182.10 | 336.80| 690.19|
| CPVOL | 600.07| 3755.47| 54.55| 106.08| 198.43 | 419.81| 969.67|
| CVOL  | 48.00| 25.09| 22.74| 30.05| 41.89  | 59.81| 81.66|
| EBA   | 3.91 | 2.51| 1.68 | 2.26 | 3.24   | 4.81 | 6.92 |
| EDV   | 1078.46| 3755.47| 20.47| 64.73| 223.43 | 784.66| 2438.12|
| ILLQ  | 0.17 | 1.11| 0.00 | 0.00 | 0.02   | 0.08 | 0.31 |
| ISKW  | 0.15 | 0.90| -0.83| -0.32| 0.13   | 0.61 | 1.17 |
| IVOL  | 2.20 | 1.79| 0.76 | 1.11 | 1.73   | 2.74 | 4.13 |
| MCAP  | 6771.90| 24004.67| 185.46| 438.59| 1256.08| 3926.04| 12837.54|
| ODV   | 13.21| 178.98| 0.01 | 0.06 | 0.39   | 2.69 | 14.65|
| PVOL  | 48.75| 25.68| 23.14| 30.47| 42.46  | 60.62| 82.90|
| RET   | 0.96 | 15.79| -14.84| -6.23| 0.67   | 7.40 | 16.08|
| RVOL  | 2.82 | 2.15| 1.09 | 1.53 | 2.28   | 3.47 | 5.13 |
Table II:
Relationship Between Insider Trading and Option Market Sentiment.

This table presents regressions of the net ratio (NBR) on the volatility spread (VS) and year and firm fixed effects. Column (1) reports the regression coefficients for the entire sample. Columns (2) and (3) report the regression coefficients for the sub-samples of small and large firms, respectively. We sort firms into large and small categories each month using the median value of market equity as the cut-off point. Columns (4) and (5) report the regression coefficients for the sub-samples of value and growth firms, respectively. We sort firms into the value and growth categories each month using the median value of the book-to-market ratio as the cut-off point. Columns (6) and (7) report the regression coefficients for the sub-samples of the winner and loser stocks, respectively. We sort firms into the winner and loser categories each month using the median value of the return over the previous six months as the cut-off point. Columns (8) and (9) report the regression coefficients for the sub-samples of high and low idiosyncratic volatility (IVOL) stocks. We sort firms into the high and low IVOL groups each month using the median value of IVOL as the cut-off point. Columns (10) and (11) report the regression coefficients for the sub-samples of stocks with high and low liquidity. We sort firms into the high and low liquidity categories each month using the median value of the Amihud (2002) illiquidity measure as the cut-off point. At the bottom of the table, we report the differences in the coefficients on VS between the groups and the corresponding test statistics. In parentheses, we report \( t \)-statistics based on robust standard errors clustered at the firm level, except for the bottom row where \( \chi^2 \)-statistics are reported. The sample period is from January 1996 to December 2017. Detailed descriptions of the variables can be found in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|------|
| VS  | ALL | SMALL | LARGE | VALUE | GROWTH | WINNERS | LOSERS | HIGH IV | LOW IV | HIGH LIQ | LOW LIQ |
| 0.59*** | 0.69*** | 0.01 | 0.52*** | 0.64*** | 0.55*** | 0.41*** | 0.64*** | 0.57*** | -0.10 | 0.64*** |
| (7.46) | (7.54) | (0.05) | (5.89) | (4.72) | (4.00) | (5.02) | (6.12) | (3.67) | (-0.36) | (7.78) |
| Constant | -52.11*** | -42.42*** | -76.85*** | -23.98*** | -80.89*** | -62.96*** | -18.96*** | -56.84*** | -50.86*** | -81.05*** | -34.70*** |
| (-13.37) | (-6.39) | (-14.08) | (-6.14) | (-14.18) | (-11.95) | (-2.49) | (-10.57) | (-10.75) | (-18.46) | (-4.90) |
| N  | 523013 | 260528 | 260407 | 227322 | 227462 | 249669 | 249798 | 260406 | 260528 | 260525 | 260403 |
| R2  | 0.01 | 0.00 | 0.01 | 0.01 | 0.01 | 0.00 | 0.01 | 0.01 | 0.01 | 0.00 | 0.00 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Test for Difference in VS Coefficients | (2) - (3) | (4) - (5) | (6) - (7) | (8) - (9) | (10) - (11) |
| 0.68*** | -0.12 | 0.14 | 0.07 | -0.74** |
| (6.83) | (0.59) | (0.87) | (0.12) | (6.63) |
Table III:  
Common Trades of Insiders and Option Market Participants: Evidence from ISE Signed Volume.

This table presents the results of a conditional bivariate sorting on the volatility spread (VS) and net insider demand (NBR). Each month, we first sort firms into terciles based on VS. We label these OPTION NEG (bottom VS tercile), OPTION NTRL (middle VS tercile), and OPTION POS (top VS tercile). We then bin firms within each tercile based on their insider trading activity: INSIDER SELL (NBR less than zero), INSIDER NTRL (NBR equal to zero), or INSIDER BUY (NBR greater than zero). We report the average of either signed call volume ratio, signed put volume ratio, or the difference of the signed call and signed put ratio within each cell. The HEDGE portfolio takes a long position in the stocks with positive net insider demand and a short position in the stocks with negative net insider demand within each option market sentiment group. For reference, the UNCONDITIONAL row includes the results of univariate sorting on NBR. Panel A reports results using all insider trades. Panel B reports results using the insider trade filter from Cohen et al. (2012). We report t-statistics in parentheses. The sample period is from January 1996 to December 2017. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| Signed Call Ratio | Signed Put Ratio | Signed Call Minus Put Ratio |
|-------------------|------------------|-----------------------------|
|                  | INSIDER SELL     | INSIDER NTRL | INSIDER BUY | HEDGE SELL | INSIDER NTRL | INSIDER BUY | HEDGE SELL | INSIDER NTRL | INSIDER BUY | HEDGE SELL | INSIDER NTRL | INSIDER BUY | HEDGE SELL | INSIDER NTRL | INSIDER BUY |
| UNCONDITIONAL     | 0.13             | 1.49***       | 2.27***       | 2.14***     | 2.65***     | 2.06***     | 1.37***     | -1.28**     | -2.76***     | -0.79**     | 0.98        | 3.75***      |
|                  | (0.57)           | (5.69)       | (4.91)       | (4.92)      | (9.53)      | (6.42)      | (2.42)      | (-2.32)     | (-9.02)      | (-2.50)     | (1.40)      | (5.36)       |
| OPTION NEG        | -0.74***         | -0.08        | -1.41        | -0.68       | 4.11***     | 3.38***     | 3.86***     | -0.23       | -5.36***     | -3.75***     | -4.00***     | 1.26         |
|                  | (-2.05)          | (-0.26)      | (-1.45)      | (-0.70)     | (9.58)      | (8.40)      | (3.62)      | (-0.19)     | (-10.47)     | (-8.11)     | (-3.01)     | (0.85)       |
| OPTION NTRL       | -0.22            | 0.81***      | 1.14*        | 1.36**      | 3.12***     | 3.03***     | 0.86        | -2.26***    | -3.43***     | -2.39***     | 0.49         | 3.93***      |
|                  | (-0.82)          | (2.90)       | (1.72)       | (2.07)      | (10.58)     | (7.87)      | (1.28)      | (-3.52)     | (-9.41)      | (-5.30)     | (0.55)      | (4.52)       |
| OPTION POS        | 1.67***          | 3.87***      | 6.57***      | 4.90***     | 0.75*       | -0.24       | -1.29       | -2.04**     | 0.68         | 3.60***      | 7.24***      | 6.56***      |
|                  | (5.56)           | (11.48)      | (7.65)       | (5.53)      | (1.92)      | (-0.52)     | (-1.27)     | (-2.03)     | (1.49)       | (6.98)      | (5.06)      | (4.60)       |

Panel A: Full Sample

Panel B: Non-Routine Insider Trades

Panel C: Opening Options Trades Only
Table IV:
Bivariate Sorts: Future Performance of Portfolios Formed on Net Insider Demand Conditional on Option Market Sentiment.

This table presents the results of a conditional bivariate sorting on the volatility spread (VS) and net insider demand (NBR). Each month we first sort firms into terciles based on VS. We label these OPTION NEG (bottom VS tercile), OPTION NTRL (middle VS tercile), and OPTION POS (top VS tercile). We then bin firms within each tercile based on their insider trading activity: INSIDER SELL (NBR less than zero), INSIDER NTRL (NBR equal to zero), or INSIDER BUY (NBR greater than zero). We report average equal-weighted (Panel A) or return-weighted (Panel B) characteristically-adjusted returns (Daniel et al., 1997) of these portfolios over the next one, three, and six months. The HEDGE portfolio takes a long position in the stocks with positive net insider demand and a short position in the stocks with negative net insider demand within each option market sentiment group. For reference, the UNCONDITIONAL row includes the results of univariate sorting on NBR. We report t-statistics in parentheses. The sample period is from January 1996 to December 2017. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

|                          | 1-Month DGTW-Adjusted Return | 3-Month DGTW-Adjusted Return | 6-Month DGTW-Adjusted Return |
|--------------------------|-------------------------------|-------------------------------|-------------------------------|
|                          | INSIDER SELL | INSIDER NTRL | INSIDER BUY | HEDGE | INSIDER SELL | INSIDER NTRL | INSIDER BUY | HEDGE | INSIDER SELL | INSIDER NTRL | INSIDER BUY | HEDGE |
| UNCONDITIONAL            | -0.11         | 0.38***       | 0.49***       |       |         |         |         |         |       |         |         |         |       |
|                          | (-1.45)       | (3.11)        | (3.04)        |       |         |         |         |         |       |         |         |         |       |
| OPTION NEG               | -0.19*        | -0.24***      | -0.09         |       | -0.39* | -0.67*** | -0.02     | 0.37    |       | -0.30     | -1.19***  | -0.31     | -0.01 |
|                          | (-1.74)       | (0.50)        | (1.30)        |       | (-1.91)| (-4.77)  | (-0.07)   | (0.96)  |       | (-1.05)   | (-6.41)   | (-0.72)   | (-0.02) |
| OPTION NTRL              | -0.08         | 0.21          | 0.28*         |       | -0.14  | 0.43**   | 0.57**    |         |       | -0.06     | 0.07      | 0.33      | 0.39  |
|                          | (-0.88)       | (1.63)        | (1.67)        |       | (-1.01)| (2.18)   | (2.26)    |         |       | (-0.33)   | (0.52)    | (1.04)    | (0.97) |
| OPTION POS               | -0.07         | 0.63***       | 0.70***       |       | 0.18   | 0.41**   | 1.60***   | 1.42*** |       | 0.65***   | 0.55**    | 2.38***   | 1.72***|
|                          | (-0.72)       | (3.29)        | (3.48)        |       | (1.01) | (4.63)   | (3.81)    |         |       | (2.64)    | (2.39)    | (5.64)    | (3.56) |

Panel A: Equal-Weighted Portfolios

Panel B: Value-Weighted Portfolios

Panel C: Return-Weighted Portfolios
Table V:
Factor Model Regressions: Future Performance of Portfolios Formed on Net Insider Demand Conditional on Option Market Sentiment.

This table presents calendar time regressions. Each month, we first sort firms into terciles based on VS. We label these OPTION NEG (bottom VS tercile), OPTION NTRL (middle VS tercile), and OPTION POS (top VS tercile). We form the hedge portfolio that takes a long position in the stocks with positive net insider demand and a short position in the stocks with negative net insider demand unconditionally and within each option market sentiment group. We then regress the next month’s return of each hedge portfolio on the following risk factors (Fama and French, 2018): the market excess return factor (MKTRF), the size factor (SMB), the value factor (HML), the momentum factor (UMD), the profitability factor (RMW), and the investment factor (CMA). In the first two columns, we report the results for the equal- and return-weighted hedge portfolio without conditioning on option market sentiment. In the subsequent column pairs, we report the results for equal- and return-weighted hedge portfolio for negative, neutral, and positive option market sentiment. In parentheses, we report t-statistics based on Newey and West (1987) standard errors with 3 lags. The sample period is from January 1996 to December 2017. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

|                | UNCONDITIONAL | OPTION NEG | OPTION NTRL | OPTION POS |
|----------------|---------------|------------|------------|------------|
|                | (1) Equal-     | (2) Return- | (3) Equal- | (4) Return- |
|                | Weighted      | Weighted   | Weighted   | Weighted   |
| Constant       | 0.56***       | 0.53***    | 0.40       | 0.40       |
|                | (2.82)        | (2.77)     | (1.64)     | (1.56)     |
| MKTRF          | 0.03          | 0.04       | 0.04       | 0.03       |
|                | (0.59)        | (0.72)     | (0.56)     | (0.47)     |
| SMB            | 0.17**        | 0.15**     | 0.02       | 0.02       |
|                | (2.22)        | (2.05)     | (0.20)     | (0.17)     |
| HML            | 0.15**        | 0.17**     | 0.16*      | 0.18*      |
|                | (2.12)        | (2.43)     | (1.82)     | (1.95)     |
| UMD            | -0.46***      | -0.48***   | -0.43***   | -0.47***   |
|                | (-6.47)       | (-6.81)    | (-5.09)    | (-5.72)    |
| RMW            | 0.19**        | 0.20**     | 0.11       | 0.14       |
|                | (2.15)        | (2.16)     | (1.01)     | (1.05)     |
| CMA            | 0.07          | 0.06       | 0.10       | 0.11       |
|                | (0.46)        | (0.44)     | (0.68)     | (0.70)     |
| N              | 263           | 263        | 263        | 263        |
| R2             | 0.56          | 0.59       | 0.37       | 0.39       |
Table VI: Fama-MacBeth Regressions: Return Predictability of Net Insider Demand Conditional on Option Market Sentiment.

This table presents Fama and MacBeth (1973) regressions of future excess returns on portfolio indicator variables and a host of control variables. Each month we first sort firms into terciles based on VS. We label these OPTION NEG (bottom VS tercile), OPTION NTRL (middle VS tercile), and OPTION POS (top VS tercile). We then bin firms within each tercile based on their insider trading activity: INSIDER SELL (NBR less than zero), INSIDER NTRL (NBR equal to zero), or INSIDER BUY (NBR greater than zero). We end up with nine portfolios and include indicators for each portfolio in the regressions except for the OPTION NTRL×INSIDER NTRL portfolio which serves as the benchmark. First three columns report estimates based on ordinary least squares in each cross-section and the last three columns report estimates based on weighted least squares using prior month’s return as the weight. The bottom of the table provides the statistical test for the difference in coefficients across the INSIDER BUY and INSIDER SELL groups within each option market sentiment tercile. In parentheses, we report \( t \)-statistics based on Newey and West (1987) standard errors with appropriate lag truncation parameter. The sample period is from January 1996 to December 2017. Detailed descriptions of the variables can be found in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| (1) OPTION NEG × INSIDER SELL | (2) OPTION NEG × INSIDER NTRL | (3) OPTION NEG × INSIDER BUY | (4) OPTION NTRL × INSIDER SELL | (5) OPTION NTRL × INSIDER BUY | (6) OPTION POS × INSIDER SELL | (7) OPTION POS × INSIDER NTRL | (8) OPTION POS × INSIDER BUY |
|-------------------------------|-------------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| RET 1M                        | RET 3M                        | RET 6M                      | RET 1M                      | RET 3M                      | RET 6M                      | RET 1M                      | RET 3M                      |
| Equal-Weighted                | Relative-Weighted             | Relative-Weighted            | Relative-Weighted            | Relative-Weighted            | Relative-Weighted            | Relative-Weighted            | Relative-Weighted            |
| (I)                           |                               |                             |                             |                             |                             |                             |                             |
| -0.21**                      | -0.40**                      | -0.11                      | -0.53**                     | -0.64**                     | 0.30                       | -0.29**                     | -0.64**                     |
| -2.19                        | -2.16                        | -0.33                      | -2.16                       | -2.25                       | 0.24                       | -2.42                       | -2.79                       |
| (II)                          |                               |                             |                             |                             |                             |                             |                             |
| -0.29***                     | -0.64***                     | -0.87***                   | -0.42**                     | -0.69***                    | -1.85**                    | 0.08                        | -0.66                       |
| -4.42                        | -4.61                        | -3.72                      | -2.47                       | -2.70                       | -2.29                      | -0.13                       | -0.45                       |
| (III)                         |                               |                             |                             |                             |                             |                             |                             |
| -0.09                       | -0.24*                       | 0.24                       | -0.32                       | 0.05                        | 0.28                       | -0.12                       | 0.54                        |
| -1.35                        | -1.69 (0.90)                 |                             | -1.55                       | 0.16                        | 0.35                       |                             |                             |
| (IV)                         |                               |                             |                             |                             |                             |                             |                             |
| 0.23                        | 0.18                         | -0.12                      | 0.28                        | 0.34                        | 0.78                       | 0.05                        | 0.42                        |
| (1.33)                       | (0.65)                       |                             | (1.26)                       | (0.82)                       | (0.94)                      | (2.88)                       | (1.15)                      |
| (V)                          |                               |                             |                             |                             |                             |                             |                             |
| -0.18*                      | -0.12                        | 0.76**                     | -0.30                       | 0.02                        | 0.50                       | 0.05                        | 0.36                        |
| (-1.78)                      | (-0.66)                      |                             | (-1.55)                     | (0.05)                      | (1.07)                      | (-0.28)                     | (1.41)                      |
| (VI)                         |                               |                             |                             |                             |                             |                             |                             |
| 0.05                        | 0.18                         | 0.54**                     | -0.05                       | 0.36                        | 0.42                       | 0.58**                     | 2.46**                     |
| (0.63)                       | (1.15)                       |                             | (-0.28)                     | (1.41)                      | (1.07)                      | (1.64)                     | (2.00)                      |
| (VII)                        |                               |                             |                             |                             |                             |                             |                             |
| 0.11                        | 0.42                         | 0.97**                     | 0.09                        | 0.40                        | 1.30**                     | 0.58**                     | 1.45**                     |
| (1.14)                       | (1.43)                       |                             | (0.71)                      | (1.11)                      | (2.13)                      | (1.64)                     | (2.00)                      |
| (VIII)                       |                               |                             |                             |                             |                             |                             |                             |
| 0.08                        | -0.11                        | -0.35                      | 0.02                        | 0.33                        | 0.60                       | 0.54                        | (0.31)                     |
| (0.54)                       | (-0.31)                      |                             | (0.09)                      | (-0.84)                     | (0.79)                      |                             |                             |
| LOG(BM)                      |                               |                             |                             |                             |                             |                             |                             |
| 0.13**                      | 0.01                         | -0.03                      | 0.08                        | 0.06                        | 0.47                       | 0.13**                     | 0.01**                     |
| (3.25)                       | (0.07)                       |                             | (1.15)                      | (0.35)                      | (1.35)                      | (2.86)                     | (2.11)                     |
| ILLQ                         |                               |                             |                             |                             |                             |                             |                             |
| -0.13                       | -0.12                        | 0.20                       | -0.22                       | -0.11                       | 0.79                       | -0.13                       | -0.05                       |
| (-1.01)                      | (-0.37)                      |                             | (-1.65)                     | (-0.29)                     | (1.05)                      | (-1.31)                     | (-0.23)                     |
| CPOI                         |                               |                             |                             |                             |                             |                             |                             |
| 0.00                        | 0.60                         | -0.00                      | -0.00                       | 0.00                        | 0.00                       | 0.00                        | 0.00                        |
| (0.45)                       | (0.12)                       |                             | (-1.15)                     | (0.26)                      | (-1.27)                     | (2.69)                     | (2.11)                     |
| CODV                         |                               |                             |                             |                             |                             |                             |                             |
| 0.00**                      | 0.01**                       | 0.01                       | 0.01                        | 0.00                        | 0.01                       | 0.60**                     | 0.30                        |
| (2.69)                       | (2.11)                       |                             | (2.41)                      | (0.78)                      | (-0.39)                     | (1.80)                     | (1.61)                     |
| Constant                     |                               |                             |                             |                             |                             |                             |                             |
| 2.54*                       | 5.98                         | 8.71                       | 2.32                        | 7.45                        | 10.70                      | 1.80                        | (1.61)                     |
| (1.80)                       | (1.61)                       |                             | (1.58)                      | (1.60)                      | (1.20)                      |                             |                             |
| N                            | 425984                       | 418404                     | 406572                      | 425984                      | 418404                     | 406572                      | 57                          |
| R2                           | 0.07                         | 0.07                       | 0.07                        | 0.12                        | 0.11                        | 0.12                        |                             |

Test for Difference in Coefficients

III - I 0.29 0.35 -0.22 0.47* 1.00* -0.83
(1.41) (0.90) (-0.40) (1.76) (1.89) (-0.66)

V - IV 0.32* 0.42 -0.36 0.60*** 0.30 0.50
(1.80) (1.53) (-0.73) (2.67) (0.90) (0.51)

VIII - VI 0.76*** 1.57*** 1.70*** 0.72*** 0.91* 0.42
(3.83) (3.96) (3.12) (3.14) (1.84) (0.54)
Table VII: Bivariate Sorts: Future Performance of Portfolios Formed on Net Insider Demand Conditional on Lagged Option Market Sentiment.

This table presents the results of a conditional bivariate sorting on lagged volatility spread (VS) and net insider demand (NBR). Each month $t$, we first sort firms into terciles based on VS from month $t-1$. We label these OPTION NEG (bottom VS tercile), OPTION NTRL (middle VS tercile), and OPTION POS (top VS tercile). We then bin firms within each tercile based on their insider trading activity in month $t$: INSIDER SELL (NBR less than zero), INSIDER NTRL (NBR equal to zero), or INSIDER BUY (NBR greater than zero). We report average equal-weighted (Panel A) or return-weighted (Panel B) characteristically-adjusted returns (Daniel et al., 1997) of these portfolios over the next one, three, and six months. The HEDGE portfolio takes a long position in the stocks with positive net insider demand and a short position in the stocks with negative net insider demand within each option market sentiment group. For reference, the UNCONDITIONAL row includes the results of univariate sorting on NBR. We report $t$-statistics in parentheses. The sample period is from January 1996 to December 2017. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

|                      | 1-Month DGTW-Adjusted Return | 3-Month DGTW-Adjusted Return | 6-Month DGTW-Adjusted Return |
|----------------------|------------------------------|------------------------------|------------------------------|
|                      | INSIDER SELL | INSIDER NTRL | INSIDER BUY | INSIDER SELL | INSIDER NTRL | INSIDER BUY | INSIDER SELL | INSIDER NTRL | INSIDER BUY |
| UNCONDITIONAL        | -0.11         | -0.02         | 0.38***      | 0.49***      | -0.13         | -0.05         | 0.73***      | 0.86***      | 0.05         | -0.20         | 0.84***      | 0.79***      |
|                      | (-1.45)       | (-1.45)       | (3.11)       | (3.04)       | (-0.99)       | (-0.52)       | (3.63)       | (3.25)       | (0.26)       | (-1.59)       | (3.12)       | (2.22)       |
| OPTION NEG           | -0.11         | -0.21***      | 0.05         | 0.16         | -0.41**       | -0.58***      | -0.36        | 0.05         | -0.32        | -1.07***      | -0.62        | -0.31        |
|                      | (-0.98)       | (-2.72)       | (0.25)       | (0.68)       | (-2.07)       | (-1.30)       | (-1.12)      | (0.13)       | (-1.20)      | (-5.93)       | (-1.41)      | (-0.59)      |
| OPTION NTRL          | -0.14*        | 0.04          | 0.15         | 0.29*        | -0.08         | 0.15          | 0.59***      | 0.66**       | 0.08         | 0.14          | 0.22         | 0.15         |
|                      | (-1.68)       | (0.80)        | (1.27)       | (1.90)       | (-0.48)       | (1.51)        | (2.68)       | (2.38)       | (0.37)       | (1.12)        | (0.73)       | (0.37)       |
| OPTION POS           | -0.03         | 0.16          | 0.68***      | 0.71***      | 0.03          | 0.41**        | 1.63***      | 1.61***      | 0.46*        | 0.52**        | 2.45***      | 2.00***      |
|                      | (-0.35)       | (1.51)        | (3.27)       | (3.20)       | (0.15)        | (2.55)        | (4.41)       | (4.05)       | (1.90)       | (2.34)        | (5.52)       | (3.95)       |

Panel A: Equal-Weighted Portfolios

Panel B: Return-Weighted Portfolios
Table VIII:
Fama-MacBeth Regressions: Return Predictability of Net Insider Demand Conditional on Option-to-Stock Volume Ratio.

This table presents Fama and MacBeth (1973) regressions of future excess returns on portfolio indicator variables and a host of control variables. Each month we first sort firms into terciles based on the option-to-stock dollar volume ratio (O/S ratio). We label these OPTION NEG (top O/S ratio tercile), OPTION NTRL (middle O/S ratio tercile), and OPTION POS (bottom O/S ratio tercile). We then bin firms within each tercile based on their insider trading activity: INSIDER SELL (NBR less than zero), INSIDER NTRL (NBR equal to zero), or INSIDER BUY (NBR greater than zero). We end up with nine portfolios and include indicators for each portfolio in the regressions except for the OPTION NTRL × INSIDER NTRL portfolio which serves as the benchmark. First three columns report estimates based on ordinary least squares in each cross-section and the last three columns report estimates based on weighted least squares using prior month’s return as the weight. The bottom of the table provides the statistical test for the difference in coefficients across the INSIDER BUY and INSIDER SELL groups within each O/S ratio tercile. In parentheses, we report \( t \)-statistics based on Newey and West (1987) standard errors with appropriate lag truncation parameter. The sample period is from January 1996 to December 2017. Detailed descriptions of the variables can be found in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

|                      | Equal-Weighted | Return-Weighted |
|----------------------|----------------|-----------------|
|                      | (1) RET 1M     | (2) RET 3M      | (3) RET 6M      | (4) RET 1M     | (5) RET 3M      | (6) RET 6M      |
| (I) OPTION NEG × INSIDER SELL | -0.11          | -0.37           | -0.52           | -0.46**        | -0.29           | -1.08*          |
|                      | (-0.77)        | (-0.96)         | (-0.72)         | (-2.20)        | (-0.57)         | (-1.66)         |
| (II) OPTION NEG × INSIDER NTRL | -0.23**        | -0.75**         | -1.61***        | -0.23          | 1.00***         | -1.89***        |
|                      | (-2.04)        | (-2.76)         | (-3.51)         | (-1.19)        | (-2.93)         | (-3.99)         |
| (III) OPTION NEG × INSIDER BUY | 0.04           | -0.58           | -2.06***        | 0.21           | -0.53           | -0.97           |
|                      | (0.16)         | (-1.49)         | (-3.79)         | (0.73)         | (-1.27)         | (-0.61)         |
| (IV) OPTION NTRL × INSIDER SELL | -0.17**        | -0.33**         | 0.07            | -0.36**        | 0.36            | -0.35           |
|                      | (-1.96)        | (-2.17)         | (0.26)          | (-2.23)        | (0.39)          | (-0.75)         |
| (V) OPTION NTRL × INSIDER BUY | 0.49**         | 1.08***         | 1.44**          | 0.44           | 0.97***         | 0.43            |
|                      | (2.53)         | (3.06)          | (2.42)          | (1.64)         | (2.59)          | (0.44)          |
| (VI) OPTION POS × INSIDER SELL | -0.24**        | -0.58**         | -0.34           | -0.33*         | -0.52**         | -0.28           |
|                      | (-2.17)        | (-2.29)         | (-0.68)         | (-1.68)        | (-2.00)         | (-0.52)         |
| (VII) OPTION POS × INSIDER NTRL | -0.03          | -0.07           | -0.14           | 0.06           | 0.15            | -0.40           |
|                      | (-0.39)        | (-0.33)         | (-0.33)         | (0.37)         | (0.50)          | (-0.81)         |
| (VIII) OPTION POS × INSIDER BUY | 0.37**         | 1.04***         | 1.82***         | 0.24           | 1.06***         | 1.75***         |
|                      | (2.10)         | (2.78)          | (2.61)          | (1.12)         | (3.00)          | (2.44)          |
| LOG(BM)              | 0.10           | 0.39            | 0.89            | 0.14           | 0.54            | 1.47***         |
|                      | (1.07)         | (1.38)          | (1.56)          | (1.18)         | (1.46)          | (2.61)          |
| LOG(MCAP)            | -0.05          | -0.08           | -0.05           | 0.06           | 0.08            | 0.09            |
|                      | (-0.76)        | (-0.48)         | (-0.15)         | (0.83)         | (0.52)          | (0.28)          |
| RET                  | -0.02**        | -0.02           | 0.00            | -0.02**        | -0.03**         | -0.02           |
|                      | (-3.42)        | (-1.35)         | (0.05)          | (-2.25)        | (-2.05)         | (-0.73)         |
| RET(T-6,T-1)         | 0.00           | 0.00            | 0.01            | 0.00           | 0.00            | 0.00            |
|                      | (0.06)         | (0.09)          | (0.50)          | (0.96)         | (0.04)          | (0.35)          |
| RVOL                 | -0.20          | -0.22           | -0.14           | -0.24          | -0.44           | 0.17            |
|                      | (-1.23)        | (-0.54)         | (-0.16)         | (-1.38)        | (-1.07)         | (0.14)          |
| IVOL                 | 0.08           | -0.11           | -0.32           | 0.18           | 0.21            | -0.63           |
|                      | (0.51)         | (-0.32)         | (-0.49)         | (1.12)         | (0.53)          | (-0.55)         |
| ISKW                 | 0.13***        | 0.02            | -0.00           | 0.08           | 0.12            | 0.12            |
|                      | (3.45)         | (0.30)          | (-0.03)         | (0.97)         | (1.05)          | (0.51)          |
| ILLQ                 | -0.10          | -0.05           | 0.29            | -0.04          | 0.03            | 0.72            |
|                      | (-0.79)        | (-0.14)         | (0.42)          | (-0.21)        | (0.08)          | (1.01)          |
| CPOI                 | 0.00           | 0.00            | -0.00           | 0.00           | -0.00           | -0.00           |
|                      | (0.49)         | (0.06)          | (-0.44)         | (1.08)         | (-0.05)         | (-1.36)         |
| CODV                 | 0.00***        | 0.01***         | 0.01            | 0.00***        | 0.01            | 0.01            |
|                      | (2.80)         | (2.13)          | (1.43)          | (2.43)         | (1.57)          | (1.21)          |
| Constant             | 2.13           | 5.02            | 7.17            | -0.48          | 1.25            | 4.91            |
|                      | (1.41)         | (1.26)          | (0.99)          | (-0.27)        | (0.31)          | (0.63)          |
| N                    | 425984         | 418404          | 406572          | 425984         | 418404          | 406572          |
| R2                   | 0.07           | 0.07            | 0.07            | 0.11           | 0.10            | 0.12            |

Test for Difference in Coefficients

|                      | (III - I)      | (V - IV)        | (VIII - VI)     |
|----------------------|----------------|-----------------|-----------------|
| III - I              | 0.15           | 0.67**          | 0.61**          |
|                      | (0.66)         | (3.21)          | (3.70)          |
|                      | -0.21          | 1.41***         | 1.63***         |
|                      | (-0.56)        | (4.06)          | (5.17)          |
|                      | -1.54***       | 1.36**          | 2.15***         |
|                      | (-2.77)        | (2.44)          | (4.42)          |
|                      | 0.67**         | 0.80***         | 0.57***         |
|                      | (1.98)         | (3.25)          | (2.91)          |
|                      | -0.24          | 0.61            | 1.58***         |
|                      | (-0.49)        | (0.69)          | (4.80)          |
|                      | 0.11           | 0.78            | 2.03***         |
|                      | (0.05)         | (0.81)          | (3.85)          |

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Table IX:  
Fama-MacBeth Regressions: Return Predictability of Net Insider Demand Conditional on Option Market Sentiment in Different Sub-Samples.

This table presents Fama and MacBeth (1973) regressions of next month excess returns on portfolio indicator variables and a host of control variables. Each month we first sort firms into terciles based on VS. We label these OPTION NEG (bottom VS tercile), OPTION NTRL (middle VS tercile), and OPTION POS (top VS tercile). We then bin firms within each tercile based on their insider trading activity: INSIDER SELL (NBR less than zero), INSIDER NTRL (NBR equal to zero), or INSIDER BUY (NBR greater than zero). We end up with nine portfolios and include indicators for each portfolio in the regressions except for the OPTION NTRL × INSIDER NTRL portfolio which serves as the benchmark. Columns (1) and (2) report the regression coefficients for the sub-samples of small and large firms; columns (3) and (4) report the regression coefficients for the sub-samples of value and growth firms; columns (5) and (6) report the regression coefficients for the sub-samples of winner and loser stocks; columns (7) and (8) report the regression coefficients for the sub-samples of high and low idiosyncratic volatility stocks; columns (9) and (10) report the regression coefficients for the sub-samples of high and low liquidity stocks. The subsamples are created by sorting stocks each month according to relevant characteristics (size, book-to-market ratio, past six-month return, idiosyncratic volatility, and Amihud (2002) illiquidity) and using the median cut-off. The bottom of the table provides the statistical test for the difference in coefficients across the INSIDER BUY and INSIDER SELL groups within each option market sentiment tercile. In parentheses, we report \(t\)-statistics based on Newey and West (1987) standard errors with appropriate lag length. The sample period is from January 1996 to December 2017. Detailed descriptions of the variables can be found in Appendix A.

|                          | (1) SMALL | (2) LARGE | (3) VALUE | (4) GROWTH | (5) LOSERS | (6) WINNERS | (7) HIGH IV | (8) LOW IV | (9) HIGH LIQ | (10) LOW LIQ |
|--------------------------|-----------|-----------|-----------|------------|------------|-------------|-------------|------------|--------------|--------------|
| (I) OPTION NEG × INSIDER SELL | -0.49*** | 0.03      | -0.48***  | -0.06      | -0.62***   | -0.09       | -0.13       | 0.29**     | 0.00         | -0.46**      |
|                          | (-2.62)   | (0.27)    | (-3.15)   | (-0.45)    | (-4.12)    | (-0.75)     | (-0.80)     | (-2.50)    | (0.03)       | (-3.32)      |
| (II) OPTION NEG × INSIDER NTRL | -0.36*** | -0.24***  | -0.36***  | -0.25***   | -0.38***   | -0.24***    | -0.28***    | -0.28***   | -0.32***     |
|                          | (-3.26)   | (-3.25)   | (-4.29)   | (-2.71)    | (-0.87)    | (-2.82)     | (-2.70)     | (-3.72)    | (-3.89)      |
| (III) OPTION NEG × INSIDER BUY | 0.13      | 0.16      | 0.20      | -0.11      | -0.18      | 0.51        | 0.56        | 0.11       | 0.27         |
|                          | (0.47)    | (0.61)    | (0.75)    | (-0.40)    | (-0.67)    | (1.24)      | (0.80)      | (0.48)     | (-0.07)      |
| (IV) OPTION NTRL × INSIDER SELL | -0.25     | -0.05     | -0.20*    | -0.05      | -0.13      | -0.08       | -0.12       | -0.07      | -0.06        |
|                          | (-1.59)   | (-0.73)   | (-1.93)   | (-0.58)    | (-0.99)    | (-1.02)     | (-0.96)     | (-1.00)    | (-0.74)      |
| (V) OPTION NTRL × INSIDER BUY | 0.33      | 0.17      | 0.31      | 0.21       | 0.17       | 0.38        | 0.17        | 0.17       | 0.22         |
|                          | (0.89)    | (0.95)    | (1.59)    | (0.77)     | (0.69)     | (1.43)      | (0.50)      | (0.96)     | (1.24)       |
| (VI) OPTION POS × INSIDER SELL | -0.36**   | -0.13     | -0.30**   | -0.07      | -0.22      | -0.10       | -0.26       | -0.12      | -0.35*       |
|                          | (-2.06)   | (-1.33)   | (-2.22)   | (-0.46)    | (-1.41)    | (-0.78)     | (-1.53)     | (-1.18)    | (-1.97)      |
| (VII) OPTION POS × INSIDER NTRL | 0.03      | 0.03      | 0.01      | 0.08       | 0.04       | 0.09        | 0.01        | 0.10       | 0.00         |
|                          | (0.27)    | (0.34)    | (0.14)    | (0.68)     | (0.41)     | (0.41)      | (0.78)      | (0.19)     | (1.23)       |
| (VIII) OPTION POS × INSIDER BUY | 0.69**    | -0.01     | 0.61**    | 0.58**     | 0.58***    | 0.59*       | 0.86***     | 0.05       | -0.04        |
|                          | (2.46)    | (-0.05)   | (2.27)    | (2.15)     | (2.67)     | (1.75)      | (3.19)      | (0.21)     | (-0.19)      |
|                          | (0.27)    | (0.34)    | (0.14)    | (0.68)     | (0.41)     | (0.41)      | (0.78)      | (0.19)     | (1.23)       |

Constant 1.70 3.21** 3.94*** 1.88 2.53* 1.64 2.30 2.62** 2.79 2.91

|                          | (0.61)    | (2.54)    | (2.69)    | (1.24)     | (1.74)     | (1.17)      | (1.28)      | (2.42)     | (1.63)       | (1.07)       |

N 218315 207669 214668 211316 213031 212953 220727 203912 211071 214913
R2 0.05 0.10 0.07 0.07 0.07 0.07 0.05 0.07 0.10 0.05
Controls Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes

Test for Difference in Coefficients

|                          | (I) - (III) | (VI) - (IV) | (VIII) - (VI) |
|--------------------------|------------|-------------|--------------|
| III - I                  | 0.62*      | 0.13        | 0.68**       |
|                          | (1.97)     | (0.50)      | (2.37)       |
|                          | -0.05      | -0.17       | (3.18)       |
|                          | 0.44       | (1.38)      | (1.43)       |
|                          | 0.59       | (1.18)      | (1.62)       |
|                          | 0.36       | (-0.08)     | (-2.35)      |
|                          | 0.40       | (-0.08)     | (-2.35)      |
| V - IV                   | 0.58       | 0.22        | 0.51**       |
|                          | (1.52)     | (1.22)      | (2.27)       |
|                          | 0.27       | (0.99)      | (1.12)       |
|                          | 0.30       | (1.74)      | (1.85)       |
|                          | 0.46*      | (1.32)      | (1.51)       |
|                          | 0.29       | (1.51)      | (1.49)       |
| VIII - VI                | 1.05***    | 0.12        | 0.91***      |
|                          | (3.69)     | (0.51)      | (3.35)       |
|                          | 0.65**     | (2.22)      | (3.12)       |
|                          | 0.80***    | (1.90)      | (3.80)       |
|                          | 1.13***    | (0.74)      | (0.26)       |
|                          | 0.17       | (3.76)      | (3.76)       |
Table X:
Fundamental Information and Contrarian Behavior.

This table presents fixed-effects logit regressions of insider buy (BUY) or sell (SELL) indicators on historical earnings measures and controls. Each month, we first sort firms into terciles based on the volatility spread (VS). We label these OPTION NEG (bottom VS tercile), OPTION NTRL (middle VS tercile), and OPTION POS (top VS tercile). Columns 1 to 4 show the relation between insider trading dummies and earnings measures conditional on negative option market sentiment (OPTION NEG). Columns 5 to 8 and 9 to 12 repeat the regressions for stocks with neutral and positive option market sentiment, respectively. SUE represents standardized unexpected earnings from the most recent announcement prior to the generation of the signals. MEET is a dummy variable that equals 1 if earnings per share from the most recent announcement prior to the generation of the signals exceeded or equaled the consensus forecast. MISP is the Stambaugh and Yuan (2016) proxy for mispricing. RET(T-6, T-1) captures historical performance. LOG(BM) and LN(MCAP) represent logarithms of the book-to-market ratio and firm size, respectively. We report t-statistics in parentheses. Detailed descriptions of the variables can be found in Appendix A. The sample period is from January 1996 to December 2017. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

|          | SELL | SELL | BUY | BUY | SELL | SELL | BUY | BUY | SELL | SELL | BUY | BUY |
|----------|------|------|-----|-----|------|------|-----|-----|------|------|-----|-----|
| **SUE**  | 0.03*** | -0.03*** | 0.03*** | -0.03*** | 0.03*** | -0.03*** | 0.03*** | -0.03*** |
|          | (9.26) | (-5.41) | (9.79) | (-5.48) | (9.47) | (-6.79) | (9.47) | (-6.79) |
| **MEET** | 0.18*** | -0.21*** | 0.21*** | -0.21*** | 0.21*** | -0.21*** | 0.21*** | -0.21*** |
|          | (7.81) | (-5.45) | (10.54) | (-6.02) | (10.54) | (-6.02) | (10.54) | (-6.02) |
| **MISP** | -0.01*** | 0.00 | -0.01*** | 0.01*** | 0.01*** | -0.01*** | 0.00*** | -0.00*** |
|          | (-6.62) | (-0.33) | (-6.84) | (3.45) | (2.81) | (-6.84) | (3.45) | (2.81) |
| **RET(T-6,T-1)** | 0.01*** | -0.01*** | 0.01*** | -0.01*** | 0.01*** | -0.01*** | 0.01*** | -0.01*** |
|          | (27.20) | (-20.74) | (30.07) | (-14.65) | (30.07) | (-14.65) | (30.07) | (-14.65) |
| **LOG(BM)** | -0.06*** | -0.12*** | -0.11*** | -0.08*** | -0.11*** | -0.08*** | -0.11*** | -0.08*** |
|          | (-2.62) | (-3.23) | (-5.08) | (-4.02) | (-5.08) | (-4.02) | (-5.08) | (-4.02) |
| **LOG(MCAP)** | 0.80*** | -0.39*** | 0.81*** | -0.36*** | 0.81*** | -0.36*** | 0.81*** | -0.36*** |
|          | (31.47) | (-10.18) | (35.27) | (-9.17) | (35.27) | (-9.17) | (35.27) | (-9.17) |
| **N**    | 65274 | 76266 | 46395 | 55944 | 81496 | 93717 | 62724 | 73330 |
|          | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **FE Year** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **FE Firm** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
A Appendix

A.1 Variable Definitions

| Variable | Definition |
|----------|------------|
| NBR      | Net buy ratio. It is the difference between the number of shares of firm $i$ bought and sold by the insiders during month $t$, scaled by the total number of shares outstanding. Measured in percentage points. |
| VS       | Volatility spread. It is the difference between implied volatility of call and put options, averaged across call-put option pairs of firm $i$ during month $t$. Measured in percentage points. |
| BEAT     | Indicator variable that equals one when earnings per share exceeds consensus analyst forecast. |
| BM       | Book-to-market ratio calculated at the most recent fiscal year end. |
| CODV     | Ratio of monthly call option dollar volume to total option dollar volume. Measured in percentage points. |
| CPBO     | Ratio of call and put bid-offer spreads, averaged during month $t$. Spreads are relative to the mid-quote point. Measured in percentage points. |
| CPOI     | Ratio of monthly call option open interest to put option open interest. Measured in percentage points. |
| CPVOL    | Ratio of monthly call option open interest. Measured in percentage points. |
| CVOL     | Call implied volatility of the 30-day 0.5-delta point on the volatility surface, averaged during month $t$. Measured in percentage points. |
| EBA      | Equity bid-ask spread relative to closing price, averaged during month $t$. Measured in percentage points. |
| EDV      | Monthly equity dollar volume. Measured in millions of dollars. |
| ILLQ     | Monthly average Amihud (2002) illiquidity measure. Measured in basis points per one thousand dollars. |
| ISKW     | Idiosyncratic skewness calculated from the residuals of the Fama-French three-factor model estimated using daily observations during month $t$. |
| IVOL     | Idiosyncratic volatility calculated from the residuals of the Fama-French three-factor model estimated using daily observations during month $t$. Measured in percentage points. |
| MCAP     | Market capitalization at the month-end. Measured in millions of dollars. |
| MEET     | Indicator variable that equals one when earnings per share exceeds or equals consensus analyst forecast. |
| MISP     | Composite mispricing index of Stambaugh and Yuan (2016). |
| ODV      | Monthly option (call and put) dollar volume. Measured in millions of dollars. |
| PVOL     | Put implied volatility of the 30-day 0.5-delta point on the volatility surface, averaged during month $t$. Measured in percentage points. |
| RET      | Return in month $t$. Measured in percentage points. |
| RVOL     | Realized volatility calculated using daily observations during month $t$. Measured in percentage points. |
| SUE      | Standardized unexpected earnings calculated as the earning surprise divided by the standard deviation of the analyst forecasts. |